Doctoral Thesis

University of Trento
School of Social Sciences

ESSAYS ON THE EFFECTS OF HUMAN CAPITAL, INNOVATION AND TECHNOLOGY ON ECONOMIC PERFORMANCE

by

Esubalew Alehegn Tiruneh

A thesis submitted to the
Doctoral Program in Local Development and Global Dynamics
in fulfilment of the requirements for the Degree of Doctor of Philosophy
(in Competitiveness and Economic Development)

April 2014

Advisor:

Prof. Dr. Ermanno Tortia
University of Trento

Co-advisors:

Dr. Silvia Sacchetti
University of Stirling

Dr. Bettina Peters
Centre for European Economic Research

Doctoral Committee:

Prof. Bruno Dallago
University of Trento

Prof. Pier Luigi Novi Inverardi
University of Trento

Prof. Giancarlo Rovati
Catholic University of the Sacred Heart

Prof. Gianluigi Grola
University of Aosta Valley

To Mother and Father

Contents

List of Tables, Figure and Appendices

Tables

Figure

Appendices

Acknowledgements

The PhD research process is often dubbed a "lonely walk". However, the success of the process depends not only on the owner of the research but also on the involvement of experts. It is, therefore, with great pleasure that I recognize individuals whose inputs made the research reach this level.

I extend my great appreciation to Prof. Ermanno Tortia, advisor, for his consent in taking up huge responsibility. I can't thank him enough, not only for his intellectual guidance in the process of writing the thesis but also for his unreserved support and encouragement throughout the research period. I have been fortunate to work with him and am sincerely grateful for his extraordinary kindness and friendly treatment that made me happy about what I had been doing every time I met him. I have also received very useful inputs from the first co-advisor, Dr. Silvia Sacchetti for Essay I of the thesis. It has become much better due to her keen attention to detail, from which I have learned a lot—I am thankful to her, too. Dr. Bettina Peters, the second co-advisor, played a critical role in sharing her experience on the management of the huge innovation panel data. Her guidance on the selection of instrumental variables in dynamic panel models and the techniques to be used in over-identification had been so wonderful. I am thankful for her extraordinary intellectual support.

I am also grateful for the doctoral research examination committee: Prof. Stefano Schiavo, Prof. Mammo Muchie, and Dr. Udo Brixy for their interest in my work and for their very productive comments that helped improve the thesis. A special thank-you to Dr. Brixy for his sincere support in the facilitation of access to information and provision of the German panel data for Essay III, without which I would not have completed in a timely manner. I also duly acknowledge members of the doctoral committee: Prof. Bruno Dallago, Prof. Giancarlo Rovati, Prof. Gianluigi Grola, and Prof. Pier Luigi Novi Inverardi for taking part in my project and for their valuable inputs. Apart from advisors, members of the doctoral research evaluation, and the award committee; a number of researchers have had sincerely supported this research project. One of those at the Center for European Economic Research (ZEW) was Dr. Sandra Gottschalk, who facilitated the data use contract as well as provided a wonderful office for the management and analysis of the innovation panel data that

I used for Essay II. Her kind assistance was always very prompt-German culture! Martin Hud, of the same research center, was also always at my disposal, even late in the evenings. Thank you, Dr. Gottschalk and Mr. Hud, for being so honest and supportive of my work. I am also truly thankful to the researchers of the Institute for Employment Research (IAB), Nuremburg, Germany, especially to Dana Muller, Klara Kaufman, Dr. Jorg Heining, Philipp vom Berge, and Matthias Dorner, for their great support in the provision, guidance, and management of the voluminous administrative data used for Essay I and for the very friendly atmosphere they all created at the Institute. In addition, I acknowledge experts of the same institute including Prof. Dr. Joachim Moller, Dr. Wolfgang Dauth, Dr. Katja Wolf, and Dr. Annie Tubadji for their very useful technical comments. I also thank Dr. David O'Brien of the International Development Research Center (IDRC) for creating an exciting working environment at IDRC as well as for his encouragement in completing the PhD project on time.

An earlier version of essay one was presented at the "54th Annual Conference of the Society of Italian Economic Association" held at the University of Bologna (Italy) October 24–26, 2013 and part of essay two was presented at the "Six Annual Conference of the Academy of Innovation and Entrepreneurship" at University of Oxford (UK) August 29–30, 2013. I am grateful to the participants of the two conferences for the constructive comments. Indeed, presenting papers in such conferences and completing the PhD project would not have been possible without the generous grant from the University of Trento which I duly acknowledge. Also, thank-you to Davide Santuari and Nicole Bertotti for carrying out the administrative roles conscientiously and for always making me feel welcome.

Thank you to my cohorts, Gashaw, Nimol, Hattachan, Anna, Carla, and Julianna for the good time I spent with you during the first year of the PhD program. Especially to Nimol, whom I call Veblen—I did spend some great times with him in SANBA, which I hope he will never forget! I take this opportunity to wish Gashaw, Nimol, Anna, and Julianna who decided to work more on their research to have a great success in their PhD defense and endeavor.

My special thanks, however, go to my family for their unconditional moral support and endless love. I especially owe a great thank-you to my elder brother Ayehu for his consistent advice throughout my life, for the unquantifiable sacrifice, and for his unfailing support of a large family without which I would have never reached where I am today. Thank you to mother (Eniye) and to father (Abiye) for teaching me a work ethic that survived personal distractions and for knowing when to hold me close and when to let me go!

Ottawa, Canada
April 2014

Summary and Introduction

History has proven that the economic development of nations depends, to a large extent, on human capital (HC), invention, and innovation capabilities, among other things. Educated individuals have the potential to exploit resources efficiently because not only is the productivity of qualified individuals large enough to make a nation grow and prosper continuously, it also has the potential to allocate resources in the most optimal manner. More educated people have a higher probability of introducing scientific knowledge, discoveries, and innovative activities that are significant for the development endeavor of society and for the competitiveness of a nation at any time. As such, HC and innovation are considered two sides of a coin—the HC being the driver and innovation the effect, in turn ensuring economic competitiveness, sustainable growth, and nation capability building.

Actually, the role of HC as a driver of innovation and of economic performance has been acknowledged since Smith's (1776) seminal work, although the established HC theory was brought into effect in the 1960s by Becker (1960) and Schultz (1963). Since then, a number of theoretical and empirical contributions have been undertaken to understand the implications of HC on economic performance at different levels—firm, industry, national, and international. Similarly, especially after the pioneering work of Schumpeter (1934), innovation has been studied across a wide range of disciplines by estimating the economic performance impact of innovation with different methods and purposes. More importantly, following the contribution of the *Frascati Manual* and, recently, the *Oslo Manual*, which introduced standard innovation indicators and measurements, innovation studies are constantly rising.

This thesis, consisting of three essays, is about HC and innovation, issues that have been and will remain critical drivers of economic performance or competitiveness of any nation. The three essays, although discussed separately, are related and have used the dynamic panel model to estimate the cause-effect relationships of dependent and independent variables. The use

of the dynamic panel model, and particularly the system generalized method of moments (SGMM), offers a number of benefits. First, because dynamic panel estimation is based on first-difference, unobserved, fixed-specific effects such as firm or region specific effects can be purged out. Second, the model captures the cross-section and time dynamics behavior of the variables simultaneously. Third, it has the advantage of using lagged dependent variables as explanatory variable where instrumenting the lagged with own deeper lags can tackle the problem of endogeneity, which further minimizes the problem of reverse causality. Fourth, the model has the advantage of capturing the problem of omitted variables and measurement errors. Fifth, it makes few assumptions, provides consistent, and efficient estimations. For all estimations, I use autoregressive techniques to identify the lag lengths of the dependent lagged variables and to check the consistency of the model by looking at whether the sum of the coefficients of the lagged dependent variables lie between pooled OLS and within the estimator. Furthermore, I test the existence or absence of serial correlations of error terms using the Arellano-Bond first order AR (1) and second order AR (2) tests, and check for over-identification of the instruments using the Hansen test.

The first essay deals with HC, creative class, and regional economic performance. The second essay focuses on the firm performance impacts of innovation in manufacturing and service firms. The third essay provides empirical evidence on technological innovation and its implications for regional economic growth. The second paper uses annual survey panel dataset from Mannheim Innovation Panel (MIP) of the ZEW, and the first and third essays use administrative data from the Sample of Integrated Labor Market Biographies (SIAB) of the Institute for Employment Research (IAB) as well as from the Federal Statistical Office of Germany.

The main purpose of the first essay is to test the contribution of Florida (2002)thesis, which argued that creative class, expressed by occupation, is superior to conventional human capital in driving regional economic performance. To this end, the study attempted to make a comparative analysis of the impacts of human capital (expressed by education), and creative class (measured by occupation) on regional economic performance. Florida (2002) has argued that occupation, which explains the creativity, talent, and innovation capability of an individual, better explain productivity; and that this approach should outweigh that of education-based HC, which may not necessarily indicate the net performance of an individual. Most of his empirical analyses made in the United States and Canada show that the capability and talent of an individual can be better tapped on the basis of work type (occupation—whether the job is related to innovative and creative areas or

simply normal or routine types of contributions) instead of the conventional education-based measurement of HC, which does not necessarily indicate the observed creativity or innovative capability of the individual.

The motivation to undertake this research in Germany was inspired by the existence of a relatively strong regional economic landscape, which is a reflection of the clear regional economic policy compared to regions of other European countries; by the availability of rich panel data that fit into Florida's thesis; and by the absence of adequate panel data–based studies. Analysis is made at the regional level because the study was essentially testing Florida's contribution, which was framed at the regional level. As such, in an attempt to compare and contrast the implications of HC and creative class on regional economy, I posit four objectives. The first objective estimates the impacts of HC and creative class on regional GDP growth; the second estimates the influence of human capital and creative class on the employment growth of regions; the third analyzes the extent to which the creative class and HC affect wage growth; and the fourth analyzes the other creative class impacts of art experts (bohemians, or BOH). Whereas the first three objectives test Florida's theory that creative class is superior to HC in generating regional economic performance, the fourth objective tests the thesis that BOH have positive roles in attracting creative core and creative professionals (creative class).

In doing so, I categorize the creative class into creative core, creative professionals, and art experts. The creative core (CC), also called the super creative core, includes experts who work in hard sciences, engineering and technology, research, and teaching areas. These experts are registered in the Sample of Integrated Labor Market Biographies (SIAB) database as physicists, biologists, chemists, mathematicians, statisticians, geologists, computing experts, engineers, architects, faculty members, teachers, researchers, think tank workers, and information experts, all with unique codes. They are grouped as inventors and innovation experts. The second groups of employees, creative professionals (CP), are experts who are registered in the SIAB database as economists, health professionals, business analysts, juries, public service administrative workers, managers, senior officials, politicians, legislators, senior officials, business professionals, police inspectors, detectives, sociologists, and anthropologists. These groups are sometimes called associate professionals or knowledge-intensive experts because they are practical problem solvers, on the one hand, and on the other hand they are considered innovators like CCs or super CCs. The third group of the creative class includes art experts (BOH) who work as creative writers, performing artists, photographers and image and sound recording equipment opera-

tors, entertainers, sports associate professionals, and fashion and other models. Classifications into CC, CP, and BOH are based on (Boschma & Fritsch, 2009; Florida, 2002; ILO, 1993) occupation classification, and other related empirical contributions.

Human capital, which is measured by education, is divided into six categories based on German education curriculum: (a) primary, lower secondary/intermediate, or equivalent education without vocational qualification; (b) primary, lower secondary/intermediate, or equivalent school education with vocational qualification; (c) upper secondary school (Abitur) without vocational qualification; (d) upper secondary school (Abitur) with vocational qualification; (e) university of applied sciences (Fachhochschule); and (f) university degree qualification. Because having vocational training in addition to completion of lower, junior, or secondary school has a decisive factor for employment, I aggregate the six groups of education to three to fit into the standard human capital classification system as (a) primary, junior, lower secondary, and upper secondary graduates without vocational certificate (1 + 3) as (EDU1); (b) primary, junior, lower secondary, and upper secondary graduates with vocational certificate (2 + 4, EDU2); and, finally, applied sciences graduates (Fachhochschule) and non-applied science degree holders (5 + 6, EDU3).

Based on the above classifications, the study analyzes the impacts of creative class (CC, CP, and BOH) and HC (EDU1, EDU2, and EDU3) on regional economic performance (growth of GDP, employment, and wage) on the basis of rich panel data for the years 1998–2008. The estimation using SGMM reveals that the creative class (CC and CP) and HC (EDU3) are found to have a statistically and economically positive and robust impact on employment growth. I find that creative class (CC and CP) is superior to human capital (EDU3) in influencing regional employment growth, confirming (Florida, 2002) contribution. Moreover, creative class (CC and CP) and HC (EDU3) have a strong positive impact on growth of regional GDP. However, contrary to Florida's (2002) thesis, EDU3 is found to work better than creative class (CC or CP) in driving GDP growth, thus rejecting his contribution. Further, neither creative class nor human capital appears to have a better driving role in wage growth. These results show that the extent of the impact of HC and creative class differs on GDP, employment, and wage growth.

Moreover, contrary to Florida (2002) thesis, BOH have a consistent negative effect on growth of GDP, employment, and wage. It was also found that BOH do have a significant role in attracting other creative class [OCC

(CC and CP)]. Overall, the empirical evidence shows that analysis of a regional economy through the contemporary creative class (measured by occupation) can be used as an alternative approach to the conventional HC (expressed by education). Indeed, it should be well noted that creative class is not always better than HC in predicting regional economic performance, as (Florida, 2002) has argued.

The second essay provides a comparative analysis on the firm performance effects of innovation input and innovation output in 3,124 manufacturing and service firms using longitudinal data for the years 2003–2010. The survey data are annual and are collected on the basis of the guidelines of the Community Innovation Survey (CIS). Based on a review of previous literature and the CIS guidelines, I proxy innovation input by research and development (R&D) intensity, investment innovation intensity, and total innovation intensity; whereas innovation output is expressed by product innovation to firm, product innovation to market, and process innovation. Furthermore, firm performance is measured by three growth variables: employment, sales, and labor productivity. The motivation to work on innovation input versus innovation output impacts of firm performance in manufacturing and service sectors in a comparative setting is inspired by three main reasons. The first has to do with the observation that most previous studies seemed to focus either on innovation input or innovation output and its impact on firm performance, where such insights do not offer comparative knowledge on the input and output innovation impacts of firm performance. Because the present contribution uses innovation input and output as indicators of innovation, the study gives a better understanding of whether the input or output approach would better explain firm performance.

Second, only a few studies have ever analyzed a comparative study of the impact of innovation on firm performance in manufacturing and services firms. In fact, most of the studies are available in manufacturing sectors, whereas only a handful of innovation impact studies exist in service sectors, especially following CIS. The dominance of innovation-firm performance studies in the manufacturing sector has cast doubt on whether innovation can better improve performance of manufacturing or service industries. The current study intends to address the gap.

Third, I have observed that much of the available information on innovation-firm performance relationships uses short panel (three years, mostly) where such contributions can, at most, use difference GMM estimator. Because the present study has a minimum of four and maximum of eight pan-

els (unbalanced data), the data allow for using SGMM, which takes difference and level estimations simultaneously. The use of SGMM, which this study employs, provides consistent, efficient, and valid estimations where the results are reported into two parts. In the first part, I thoroughly analyze the effects of innovation input on firm performance in manufacturing and service sectors; in the second part, I discuss the innovation output effect of firm performance in both sectors.

In the first part of the analysis, I find that the first lag of employment has not only positive but also strong effects on employment growth, with the level of effect being robust at $p < 0.01$ in manufacturing and service sectors. Moreover, I observe that the elasticity of employment growth with respect to previous-year employment growth is found to be almost same in both sectors where a 1% increase in previous-year employment results in a 0.8% growth of employment in both firms. This indicates that persistent effects of employment appear to be strong enough in manufacturing and services sectors. Moreover, R&D intensity, investment innovation intensity, and total innovation intensity in their first lags have crucial impacts on employment growth in both sectors. But the extent of impacts and elasticity of employment growth differs between the two sectors. Against their lags, current R&D intensity and present investment innovation intensity have, however, had negative effects on employment in manufacturing as well as in service sectors. I also obtain that exporting and being a member of a corporate group have consistently positive and strong impacts on employment in both firms. One important distinction in the employment growth effects of innovation inputs is that it is in the service industry compared to the manufacturing firms, and its effects have been observed to be more robust, indicating that employment growth is more responsive in service firms than in manufacturing firms.

The sales growth impacts of innovation input in manufacturing and service firms also show some interesting results in that past-year sales growth has positive, robust effects on current sales growth in both sectors. Moreover, I find that with the exception of current total innovation intensity, other variables, including R&D intensity and investment innovation intensity (and their lags), export, and being a member of a corporate group, have positive effects on sales growth in both sectors. The result that total innovation intensity has a negative influence on sales growth may indicate that allocation of resources for total innovation (aggregates of R&D expenditure and investment innovation), including for hiring R&D experts, providing training services for research associates, buying research facilities, preparing conference venues, and the like, might have squeezed the sales turnover volume

as these activities normally have a tendency of shifting resources, eventually leading to negative consequences. Moreover, it is learnt that the elasticity of sales growth is much greater in manufacturing than in service industries.

With respect to labor productivity, its first lag is found to have a positive effect in manufacturing and service sectors. However, the extent of the effect varies between the two sectors because, whereas the effect is strong in manufacturing, it is weak in services. Furthermore, though the proportion of resources allocated for R&D as well as for investment innovation is found to have increased productivity in both sectors, the share of total innovation expenditure appears to be negative in both sectors. Overall, elasticity of labor productivity seems to have a slightly better response with respect to innovation inputs in service sectors than in manufacturing, demonstrating that the more R&D related investments are made, the more likely it is that productivity will grow more in service sectors.

In the second part of Essay II, I present the results of the impact of innovation output on firm performance (employment, sales, and labor productivity growth). The results show that growth of employment in the manufacturing and services sectors has been greatly influenced by product innovation to firm, product innovation to market, and process innovation. As in the case of innovation input, I observe that the state dependence (first lag of employment) has consistently positive and substantial effects on employment growth in manufacturing and service sectors. However, compared to innovation input–induced employment growth, the elasticity of employment growth is found to be greater with respect to increases in previous employment. Moreover, whereas current product innovations to firm (introduction of new or significantly improved goods and services) have extensive effects on employment, it is not possible to find strong impacts when the first lags of these variables are used. Product innovation to market in its first lag and current values—contrary to product innovation to firm—has negative feedback on employment growth in service firms. Further, I find that cost reduction innovations play a large role in boosting the growth of employment in both sectors.

In the sales growth model, its true state dependence, innovation output indicators, and a set of controls contribute enormous to sales growth in both sectors. Indeed, all innovation output indicators have enhanced sales growth, but compared to innovation input, innovation output do not appear to have strong effects. Moreover, with respect to how product innovation to firm, product innovation to market, and process (cost reduction) innovation affect firm labor productivity, I find that all of them, including their

lags, have positive (some with robust and some with non-robust) influences on labor productivity.

Overall, the estimations show that most of the true state dependence, innovation input, innovation output, and control variables are observed to have positive and robust effects on employment, sales, and labor productivity growth in manufacturing and service firms. It appears, however, that innovation input is superior to innovation output in driving employment, sales, and labor productivity growth. This implies that innovation input indicators (R&D intensity, investment innovation intensity, and total innovation intensity) are better than innovation output indicators (product innovation to firm, product innovation to market, and process innovation) in generating firm performance. Innovation input indicators are objective as they refer to expenditure on R&D, investment innovation, and total innovation whereas innovation output indicators are subjective because measurements are based on binary responses such as "yes, innovation is introduced" or "no, innovation is not introduced." The superiority of innovation input indicators compared to innovation output indicators in determining firm performance indicates that objective measurements are better than subjective innovation measurement. Moreover, the study reveals that elasticity of employment growth with respect to innovation input and innovation output differs between manufacturing and service firms.

The third essay analyzes the extent of the impact technological innovation has on the performance of regional economy based on five years of panel data drawn from the SIAB, Stifterverband, and the Federal Statistical Office of Germany. My motivation for undertaking this study emanates from two things: first, the observation that a large quantity of empirical research on the economic performance effects of innovation has focused on the micro (firm or industry) or macro (national and international) level whereas only few or no studies have focused on the meso (regional) level. However, globalization has made regions an important unit of analysis- sometimes even being more important than the country. Compared to other EU member countries, in Germany, regions and regional economic policies have gotten more recognition because of the relatively strong economy of the country; it was not even affected, practically speaking, by the recent financial crises of 2008 when the world economy was hit hard. Second, as a stylized fact, available literature uses R&D and patent rights as indicators of technological innovation. This study includes researchers, in addition to the two variables mentioned, as indicators of innovation; and in doing so, it aims at understanding innovation activities in detail and further looks at how such measurement will impact economic performance of regions.

Guided by previous economic literature, I measure regional economic performance by growth of regional per capita income (PCI), employment, and wage growth. Moreover, technological innovation is measured by R&D intensity, number of patents applied per 100,000 population, and share of researchers. Results are divided into two parts with the aim of comparing the cross-section and longitudinal results. Accordingly, the first part provides the five-year average data in cross-sectional form, and the second part provides the five-year panel data SGMM estimated results. Of all variables, the first lag of PCI is the most influential factor in affecting per capita income growth, showing the importance of the strong persistent effects of income. More specifically, a 1% increase in previous-year PCI of a region results in a 0.9% growth of PCI growth to which the effect is found to be not only positive but almost with one-to-one correspondence. Money allocated for R&D has also contributed greatly, though population growth—as pointed out by Malthus (1798) long ago—results in negative effect. In the same pattern, employment growth has been affected positively and strongly by its first lag, by the amount of capital allocated for R&D, by patent rights applied and by share of researchers—although the elasticity with which employment growth responds to these variables does vary. Moreover, wage growth has to a large extent been influenced positively by innovation but is negative when population growth is employed as covariate.

This page intentionally left blank

Essay I

Human capital, creative class and regional economic performance in Germany
A dynamic panel analysis

1.1 Introduction

The golden age of capitalism (1948-1972) recognized subnational entities or regions as the crucial building blocks of national and global economies. Consequently, a number of regional theories have been introduced in an attempt to design approaches that make regions resilient and competent with the rest of the global economy. Among the policies introduced are the seminal industrial growth policy of Isard (1960), which deals with the methods and techniques of regional analysis, including focusing on the importance of regional export capability, investigating mechanisms that increase export share of regions, and looking for options that increase the multiplier effects of regional exports. Other theories, such as location quotients[1], shift shares[2], and input-output analysis[3], have also been developed to examine regional industrial structure, industry cycles, industrial linkages, and industry-related variables, all intended to beef up the economy of regions. Indeed, many states have established industry task forces and launched strategic plans to develop specific target industries that could improve the business environment, create new jobs, and boost the overall economic performance of regions (Koo, 2005; Markusen, Wassall, DeNatale, and Cohen, 2008; Markusen, 2004).

However, observations show that knowledge economy is increasingly overtaking industrial-based development, and regions with commendable clusters of knowledge have been observed to be more innovators, frontiers of economic growth, and of growth centers for global economy. Knowledge economy is a function of well-trained, innovative, and crea-

tive people whose existence and productivity are assumed to be of high value by any measurement. In this case innovative or creative individuals, as engines of regional economy, are believed to have special category of occupations whose productivity is expected to be superior to those who hold routine types of occupations. Scholars have attempted to explain the reasons on why some occupations that apply a high content of knowledge or creativity tend to be located in particular areas and how this can serve regional markets, generate economic growth, and benefit local communities (Florida, 2003; Markusen, 2004; Sacchetti, Sacchetti, and Sugden, 2009). These authors and others argue that regional development policy need to emphasize on the role of knowledge economy including creativity,[4] innovation, trade, job expectations, and opportunities for entrepreneurship (Krugman, 1997; Markusen, 2004; OECD, 2002). Especially, Florida (2002) has devoted much on explaining creativity, innovativeness, diversity, and openness of society as the fundamental drivers of regional economic development.

In an attempt to analyze the drivers of regional economies from the perspective of knowledge economy, he measures HC through occupation instead of the conventional measure—educational attainment. He argues that it is the kind of occupation that provides creativity and innovation that is the main driver of regional economy. He calls these individuals who generate creativity and novelty the creative class. Following his insight, some scholars analyze empirically the implications of knowledge economy seen from the innovativeness and creativity view on regional economy. This is done using a selective approach, going from encompassing perspectives that look at the creative content of any job in any sector to a consideration of specific occupations characterized by a high degree of creative content. These are occupations defined by an ability to identify and problematize a situation in a particular domain in a new and relevant way, thereby, transforming inter-subjective understanding into new action and, therefore, bringing something into existence using intelligence and imagination (Boschma and Fritsch, 2009; Möller and Tubadji, 2009; Sacchetti and Tortia, 2013). In order to identify creative occupations, these scholars refer to the concept of the creative class defined by Florida (2002) which includes professions where the scope of the job allows for identifying problems, proposing new solutions, or combining existing knowledge in new ways. He focuses on the creative content of individual occupations rather than industrial sectors as an in-

tegral part of ensuring economic growth. This crucial message is also discussed by Markusen (2004), who establishes that the utility of targeting occupations is in their ability to transversally generate positive territorial externalities by stimulating entrepreneurship, recruiting and retaining talent, and serving multiple industrial sectors. Industrial classifications, moreover, would underestimate the presence of artists tout court. Within this approach, occupational measures (Standard Occupational Codes, or SOC) are argued to be best positioned to measure creative occupations, not only with respect to conventional industrial measures (Standard Industrial Code, or SIC) but also with respect to education, the other major indicator of HC.

Measuring HC by occupational activity apart from using education attainment as established long ago by Becker (1960) and Schultz (1963) can provide different interpretations on regional economic analysis. This is because the occupation vs education measurement of human capital can reveal different conceptual approach. Take, for example, the classic work by Sen (2002) on function (to be understood as outcomes, or people "doings") and capabilities (the freedom to achieve a particular functioning). When focusing on education, the HC approach gives attention to one specific functioning or outcome, which is the *analytical skill* achievement, regardless of its creative content and *actual application* to production activities. Conversely, by focusing on occupations, the creative class approach directs attention to another type of functioning, that is, the *creative achievement*, regardless of the actual education achievement. Occupational achievements, from this perspective, are an indication of the *real doings* of individuals in their job positions, where they can apply and regenerate knowledge, critical thinking, and skills, potentially creating spinoffs and additional occupation. Education, on the other hand, can be regarded as an outcome that measures a potential occupation and does not necessarily overlap with doings or the use of the skills learned, such as when educated individuals are unemployed or underutilized within their occupational role.

Occupations that provide creativity and novelty capture individuals who may not have a higher education degree (e.g., a self-taught manager and policy maker) and whose work is valued for skills developed in the creative practice of the profession or arts. Indeed, Florida (2002) takes occupational activity compared to education as a better driver of the presence of industrial activities that can absorb a creative and skilled la-

bor force. In this sense, HC (educational skills) and the presence of a regional industrial base are complementary aspects of a knowledge-based economy: you need skills to transform creativity into a tangible output; you need creativity and critical judgment abilities to make your skills applicable; you need a production outlet to have an opportunity to apply your skills optimally. He also argues that creativity which is a function of occupation is very much consistent with educational skills.

Taking his insight as a very important piece of work, this essay seeks to provide a comparative analysis of the impact of creative class and HC on the economic performance of administrative regions (NUTS3) in Germany using panel data over the years 1998–2008. The study attempts to answer the following questions: Is creative class superior to HC in driving regional economy? To what extent do creative class and HC impact the economic (GDP) growth of regions? How big is the impact of creative class and human capital on regional employment growth? Does regional wage growth respond with respect to creative class and HC differently? Do BOH attract other creative class [OCC (CC+CP)]?

This essay, including the preceding introduction, has seven parts. The foregoing has highlighted the creative class and HC as drivers of regional economy. In the following, I provide conceptual issues of creative class as framed by Florida (2002), the criticisms on his contribution, theoretical reflections of the creative class along with some empirics. In the third section attempt is made to explain how the present study differs from the previous studies and in doing so in what way the contribution add values to existing knowledge of creative class vs HC as drivers of growth. In the fourth part, I present the econometric model and estimation strategies used to estimate and compare the impacts of creative class and human capital on regional economy. Descriptions of panel data and summary statistics are presented in part five while interpretations of the estimation results are made in part six. Finally, I provide a conclusion.

1.2   Creative class: Concept, theory and empirics

1.2.1 Concept and critiques

The creative class concept refers to people who are engaged in complex problem solving areas that involve a great deal of independent judgment and require high levels of intellectuality. These people are primarily paid to create and have considerable autonomy and flexibility than others

(Florida, 2007). He divides the creative class into CC and CP where the former contain scientists and engineers, university professors, poets and novelists, artists, entertainers, actors, designers and architects, as well as thought leadership of modern society: including nonfiction writers, editors, cultural figures, think tank researchers, analysts and other opinion makers. Whether they are software programmers or engineers, architects or filmmakers, they are fully engaged in the creative process (Florida, 2005) . The outcomes are new forms or designs that are readily transferable and broadly useful-such as designing a product that can be widely made, sold and used; coming up with a theorem or strategy that can be applied in many cases; or composing music that can be performed again and again. Along with the CC are the CP who work in a wide range of knowledge-intensive industries such as in high-tech sectors, financial services, legal and healthcare professions, and business (Florida, ibid). The CP has a strong overlap of creative experts with educational achievements. These people, according to him, are engaged in creative problem-solving, drawing on complex bodies of knowledge to solve specific problems. Doing so typically requires a high degree of formal education and, thus, a high level of human capital.

Florida's contribution appears to be impressive and an alternative approach, replacing HC with creative class, which centers on who does what (occupation) instead of the conventional educational qualification that is not necessarily indicative of an individual's real activity. However, creative class has received a number of criticisms, regarding (a) the elusiveness of the creative class concept, (b) the causal relations and interpretations of creative class, and (c) the policy implication of the creative class (Andersen, Hansen, Isaksen, and Raunio, 2010). In a similar tone, Asheim and Hansen (2009) recommended breaking creative class into less heterogeneous subcategories to better understand the dynamics of the knowledge economy; else, it is not possible to guarantee that all groups of creative class will have same preferences—for example, either all would like to live in places where the people are nice or in places where there is a conducive business climate. Another comment regarding the elusive concept of creative class was made by Glaeser (2005), who addressed the similarity between creative class and HC. Based on evidence of strong associations between highly educated people and regional growth, he argued that Florida (2002) gives the creative class credit for causing regional growth where growth is actually generated by HC.

On causal relations, Florida has been attacked on the basis of the un-convincing causal relationships of creative class and economic growth that he established. In this regard, Scott (2006) argued that Florida did not describe the conditions necessary and sufficient to make creative in-dividuals come together and remain in a particular place over a reasona-bly long period of time. Scot further brought into attention that entre-preneurial and innovative energies are stimulated by a differentiated local production system favoring the importance of a business climate as a source for innovativeness rather than just people climate[5]. By this, Scott maintained that it is business that generates economic growth and not necessarily creative people who produce growth. Indeed, Florida's con-cept appears to focus on a very small part of the economy when empha-sizing the high-tech industries as prime economic drivers that account for about 8% of the total employment and, thus, probably left out some very important dynamics of the economy. Moreover, Hansen and Niedomysl (2009) indicated that people in the creative class are slightly more selective in their choice of destination compared to people outside the creative class. They demonstrated that people belonging to the crea-tive class in Sweden move for jobs rather than attractive neighborhoods, indicating that the causal relation in the Swedish context favors people moving for jobs rather than jobs moving for people.

As per policy implications, the creative class approach of regional economic development appears to have a supply-side policy. It draws policy prescriptions on the basis of rather simple theoretical underpin-nings and unconvincing justifications. Following Florida's creative con-cept, creative city ideas have been applied by policymakers, including those in Nordic city regions. Peck (2005) has warned that the tendency to put Florida's ideas into practice as supply-side policy merely to satisfy creative employees is dangerous. The idea that creativity increases the competitiveness of cities sustainably does not take into account the structural differences of cities, historical variations, power of the life cy-cle that cities which have been more prosperous and creative once could fall into being decayed and unattractive, and the possibilities of the pow-er of other explanatory variables that could shape cities the way they are. The creativity-driven policy prescriptions for cities seem to end up hav-ing the same method of city competitiveness, which is not convincing. Although Peck accepted the role that creative class and creativity play in economic development efforts, creative class-based economic policy can

lead to problems, including the race to attract talent and mobile workers, that may divert attention from important local challenges such as large socioeconomic inequalities. Moreover, it is very likely that many regions will focus on the same types of policy initiatives in order to attract highly educated people. Such an attempt, in reality, is hard to implement.

The present study recognizes Florida's contributions as well as the criticisms he received. Based on his contributions and other subsequent literature's profession classification system (Boschma and Fritsch, 2009; ILO, 1993), this study has organized the creative class into three groups as shown in Table 1.1. In Germany, each occupation or profession is assigned three-digit number that provides a unique opportunity in analyzing the implications of creative class on regional economies.

Table 1.1
Creative class by occupation

Creative people	Experts classified by occupation
Creative core: CC	Physicists, chemists, biologists, mathematicians, statisticians, geologists, computing scientists, engineers, architects, professors, faculty members, researchers, think tank experts, data, information experts, writers, poets and the related.
Creative expert: CP	Economists, decision scientists, legal scientists, health professionals, high level politicians, senior officials, business experts, intelligence and detective workers, social workers, and anthropologists.
Art experts: BOH	Photographers and image and sound recording equipment operators, performing artists, artistic, entertainment and sports associate professionals, fashion and other models.

Source: Author's construction using Boschma and Fritsch (2009), Florida (2002), ILO(1993)

The classification of the creative class into three categories and the comparison of this classification with human capital (education-based classification) for regional economic analysis require HC to be classified into three groups. However, Germany's curriculum of education is divided into six levels or types. The first level or type contains those of primary, intermediate, and lower secondary school graduates without vocational certificates; the second level includes primary, intermediate, and lower secondary school graduates with vocational certificates; the

third level includes upper secondary school graduates without vocational training; the fourth level has upper secondary school graduates with vocational training; the fifth level is for university of applied science holders; and the sixth level includes non-applied science degree holders. Experience proves that the classification of the German education system into six categories does not make sense for empirical analysis because there is no real difference between some of the categories. As such, the six groups are merged into three with the purpose of making the comparison with the creative class more appropriate, as indicated in Table 1.2. In doing so, graduates without vocational certificates are categorized into group 1 (EDU1), those with qualifications with vocational certificates into group 2 (EDU2), and University of applied science and non-applied science degree holders into a third group (EDU3).

Table 1.2
Human capital by educational attainment in Germany

Human capital	Educational attainment
EDU1	Primary, intermediate, lower secondary, and upper secondary school graduates without vocational certificates (1 + 3)
EDU2	Primary, intermediate, lower secondary, and upper secondary graduates with vocational training (2 + 4)
EDU3	University of applied and non-applied science degree holders (5 + 6)

Source: Author's construction on the basis of SIAB (2013).

1.2.2 Theory and empirical insights

The central indicator of the creative class is creativity measured by innovative occupation[6] where its impact on economic growth has been acknowledged by scholars including Mathur (1999), Theodore and Carlson (1998), and Thompson and Thompson (1985), although the popular recognition of creative class has been identified following Florida's best-selling book, *The Rise of the Creative Class: And How It's Transforming Work, Leisure, Community, and Everyday Life*. The main aspect of the insight lies in the assumption that creative is superior to HC (measured by education) in generating regional economy. The theory also claims that unlike main-

stream economics- which takes growth performance of regions as a function of business climate- regional economic development needs to be approached from a region's capability to attract talented individuals through availability of amenities and openness of society. This tenet can be articulated into three main theories. The first states that creative class is the crucial driver of regional economic development. The second focuses on the economics of location of specific factors (regional features) that attract creative class. The third addresses the economics of BOH and their impact in attracting other creative class. I focus on the first and third tenets because the aim is to analyze the distinctive impacts of creative class occupations on the one hand and education on the other on economic growth as well as how BOH affect other creative classes.

Creative class is a motor for regional economic development

The central idea in this theory is that creative class is taken as a critical engine of regional economic development. Proponents of this theory support the view that creative class outperforms education as a measure of HC in boosting the productivity and competitiveness of a region. A region with a good number of creative or innovative people tends to be competent sustainably (Markusen, 2006). Such contexts imply that regional economic growth is not primarily based on particular industries, such as high-tech industries, operated by high level HC but are rather based on creative people who are not tied to a specific industry. This thought seems to undermine sector-based regional economic development, taking the emphasis off the role of agglomeration externalities, regional specialization, or localization economies (Glaeser et al., 1992).

The creative class approach differs from industry-driven regional development in that the latter emphasizes knowledge spillovers between firms and industries. Besides, whereas the conventional industry approach takes sectorial innovation as a precondition for regional economic development, a creative occupation approach considers the creative class's capability to generate innovation a preferred way of sustaining regional economic development (Stolarick and Florida, 2006). This view supports the works of Zucker, Darby, and Brewer (1998) and Almeida and Kogut, (1999), who concluded that the transfer of knowledge and skills embodied in people, instead of firms, is crucial for economic growth and spillover.

The theorized relationship between creative class and economic growth is praised by some scholars as an improvement of the method used to examine the relationship between HC and regional economic development (Marlet and Woerkens, 2004). Creative class indicates economic performance via occupational outcomes and, therefore, better explains economic growth than the traditional means of educational attainment, in which accumulation of innovative capital is to depend on formal education through codified knowledge and formal training. Indeed, HC *per se* cannot contribute to regional economic development if training is not implemented in appropriate job (i.e., if what one knows is not practiced). It is the capability to create ideas, inputs, processes, and products that matters more for economy. The claim supports the view that regions with concentration of creative occupations are likely to generate innovation in any sphere of society through new ideas, concepts, or technologies and increase propensity of entrepreneurial atmosphere, which is seen as a requirement for sustained economic advancement.

A number of studies have attempted to test this theory, though perhaps with questionable methods. These include the works of Mellander and Florida (2011), who analyze the implications of creative class, super creative, and CP against the conventional educational attainment on wages per capita in Sweden, where wage measures regional growth. The findings revealed that creative class outperforms conventional educational attainment of HC. Furthermore, occupations in the arts and culture play a significant role. These results are consistent with Marlet and Woerkens (2004), who argued that occupational measures may well set a "new standard" for measuring HC and deserve attention in regional growth studies.

Likewise, the study of Florida, Mellander, and Stolarick (2010) on Canada's regional growth between 2001 and 2006 also shows that educational attainment and creative class are strongly associated and have positive impacts on regional income. Nevertheless, whereas the creative class is found to have a significant impact on regional income, education doesn't have a major impact. Of the two main groups that make up the creative class, CP are more strongly related to regional income than the CC. Similar results were observed by Mellander and Florida (2007) and Stolarick and Florida (2006). Moreover, Florida et al. (2010) found that creative class outperforms conventional educational attainment when

measuring regional labor productivity by wages, whereas conventional education measures of human capital better measure regional income.

The superiority of the creative class compared to HC as a driver of regional growth is also supported by other studies, including the contribution by Boschma and Fritsch (2009), who conducted a cross-country study of creative class versus HC and their impact on regional economic performance in over 450 regions of seven European countries. The results reveal a positive, robust effect on employment growth and new business formation. This result supports the theory that occupation-based creative class indicator is a more significant measure for HC than formal education. Although it supports Florida's view, the corroboration is based on simple regression model that does not account for endogeneity because analysis is based on cross-sectional data, which are not able to capture the cross-section and time dynamics across periods. A recent contribution of Tiruneh (2014) in Italy supported Florida's theory that the share of creative class and the share of creative professionals are superior to the share of university graduates in driving regional economy. He also found a strong positive correlation between CC and HC.

On the other hand, Lengyel and Ságvári (2011), who estimated effects of educated labor force and creative occupations on regional development in Hungary using cross-sectional data, found that the share of educated labor compared to the share of creative professionals has a bigger effect on growth of regional economy. This supports the classical theory that HC measured by education plays a major role in economic development, as opposed to the views of Florida and his empirical findings (Florida, Mellander, and Stolarick, 2008; Mellander and Florida, 2011). Perhaps the most comprehensive analysis, with respect to the implications of creative class on regional economic growth, comes from Möller and Tubadji (2009), who employed a dynamic panel. The study was limited to West Germany for a period of 30 years, collapsed into five panels. They-like Boschma and Fritsch (2009)-separated BOH from the rest of the creative class in order to study the separate effects of BOH and the sciences. This way, they found that agglomeration of creative class (CC, excluding artists and CP) increased the propensity of economic performance of a region and outperformed conventional indicators of HC. Nevertheless, the estimation does not support another of Florida's views—that creative workers flock where BOH live. Furthermore, Möller and Tubadji found that creative class is instead attracted by favorable

economic conditions, such as employment or wage. By the same token, Hansen and Niedomysl (2009)'s analysis of the effects of creative class on regional economy showed that the relationship between regional economic performances, the creative class, people, and business climate are positive. Although larger regions favor Florida's arguments, the findings from smaller regions do not support them.

Some recent studies provide evidence that the creative class compared to the non-creative class has found to be the least affected in unemployment during the financial crises. For example, Gabe, Florida, and Mellander, (2013) using individual level data from 2006–2011 US Current Population Surveys show that members of the creative class had a lower probability of being unemployed over financial crises period than individuals in the service and working classes and that the impact of having a creative occupation became more beneficial in the 2 years following the recession. These patterns, if they continue, are suggestive of a structural change occurring in the US economy—one that favors' knowledge-based creative activities.

Similarly in an attempt to understand the economic effects of the creative class after the financial crisis Currid-Halkett and Stolarick (2013) looked at the regional unemployment variation in the years 2007–2011 against baseline unemployment in 2005, to study if specific subgroups within the creative class have different relationships with regional unemployment. Throughout the entire period they found that all of the creative subgroups are associated with lower unemployment, that creativity matters but the influence of each subsector is dependent on region size.

Creative class flocks to where art experts live

Florida (2002, 2007) identified that where there are more bohemians (BOH), there will also be more other creative class (OCC)—the former attracting the latter. This theory was constructed based on the observations of large urban regions of the United States, with a population of more than 100,000. The approach, having been framed for large urban regions, is more suited for regions whose population is large enough, making the application of the theory in rural regions or in regions with small urban sizes difficult, if not impossible. This begs the question concerning the relation between the creative class and rural economic development as well for regions with small urban areas, such as in many European countries whose urban areas are small compared to urban areas

in the United States or Canada, where Florida espoused his theory. Some studies have, indeed, supported the theory that BOH do attract and have substantial implications on the distributions of the CC and CP in regions as well as in urban areas. For example, Fritsch and Stützer's (2012) estimation of the effect of BOH on CC and CP in Germany revealed a positive and significant effect. This study, however, uses cross-sectional data and, therefore, the positive impact of BOH on creative class cannot be taken for granted for the estimation is not in a position to capture reverse causality or endogeneity-one of the critical problems. Moreover, the estimation is underspecified.

An important contribution related to art experts or activities-other creative class relationship is that of tolerance effect. The literature on this argues that other creative class would prefer to live (as anyone would do) in places where there is better tolerance among individuals. In this regard, Qian (2013) found a positive association between tolerance (but not necessarily diversity) and creative class in a multivariate context and creative class further demonstrates a positive effect on both innovation and entrepreneurship. However, arts-related employment is found to be highly concentrated in the very largest urban centers. This further suggests that the bigger the city the more is the likely to find a large number of other creative class people. Smaller places with particular attributes (attractive natural setting, proximity to large urban centers) are increasingly successful in attracting arts-related activities, art experts, as well as other creative class but such is not necessarily associated with stronger employment growth or the development of knowledge-rich industries(Polèse, 2012)

The studies of Boschma and Fritsch (2009), which used cross-sectional data for a large number of regions in Europe, reveal that BOH attract CC and CP as well as other creative class (OCC) to a significant level. Moreover, Florida (2002; 2003; 2005) shows that BOH play an important role in regional economy, not only by being involved in innovative activities by themselves but also by creating an atmosphere that attracts other intellectuals with ripe talent in solving many regional social and economic problems. The people who have this talent are most often the creative class. Nevertheless, Glaeser's (2005) evidence comes with a contradiction: that BOH do not have any substantial effect on the distribution of other creative class in a regional or urban setup. This is at odds with Florida's popularization of creative class theory, and Glaeser de-

fended the idea that the creative class is just a HC surrogate. Also, Möller and Tubadji (2009) rejected the view that Bohemians attract a large share of the creative class and instead noted that the labor market and other incentives play positive roles in attracting the labor force of the creative class. Furthermore, they argued that the decision to move into a new place is not influenced by the presence of BOH but by other economic factors.

1.3   Contribution of the study

The present research takes Germany as a case study because of the existence of a relatively large number of regions with better economic performance compared to other European country regions, existence of strong regional economic policies, and the availability of panel data that fit into Florida creative class concept. This paper intends to contribute to the growing creative class versus HC-driven economic performance debate in the following ways: First, although the impact of HC on regional economic performance in Germany and elsewhere has actually been analyzed by a number of scholars, such contributions have measured HC primarily through conventional educational qualification—a classical and still most-used measure, which does not take into account the creative class method. The current study intends to address this gap by measuring HC through educational qualification as well as a variant of HC—that is, creative class by occupation—and estimate how the two approaches affect regional economy. In this respect, estimating regional economy through Becker's (1960) and Schultz's (1962) HC or through Florida's creative class method will help to appreciate the regional economic growth impacts of education-based and occupation-based approaches.

Second, analysis of regional economic performance through occupation instead of education qualifications appears to be researched comprehensively neither in Germany nor in any other country. The few available studies overwhelmingly indicate that creative class occupations seem to greatly boost the economic performance of regions, notwithstanding the fact that these studies are not based on comprehensive data or information. Consequently, they lack replicable lessons and insights for regional labor market and economic policy implications. The current study, using a rich panel data set and rigorous model, intends to address this, at least in the context of Germany.

Third, regional economic development is increasingly becoming dependent on knowledge as well as on innovation, which are, in turn, reflections of individuals' creative ability or educational attainment. As already discussed, creativity (creative occupations) defines the actual ability of individuals to apply knowledge, exerting critical judgment and intuition to economies in a way that education cannot do, as it mainly reflects competence with respect to codified or analytical knowledge. Analysis of regional economies through creative occupation and educational attainment will, therefore, help to identify whether the creative class or HC is a better indicator of knowledge economy. In addition, a study of creative class–driven regional economy could also provide insight into identifying the kind of occupations that contribute more to regional economic performance (growth of GDP, employment, and wage).

A final contribution is in the use of a rich longitudinal data set as well as a dynamic panel model. Previous creative class studies have mainly been concerned with the associations between creative class and regional economic growth. Besides, the estimation of the regional economic development effects of the creative class, including many of Florida's and related works, employs simple regressions of cross-sectional data. These attempts do not capture unobservable regional fixed effects, endogeneity problems, or time dynamics. Because the present study uses rich administrative panel data of 11 years, the result of such detailed information would allow for estimating both cross-sectional features and time series dynamic effects of the creative class on regional economies. Besides, the use of dynamic panel—and, in particular, the use of generalized methods of moments (GMM)—addresses endogeneity and reverses causality issues where previous studies fail to capture. In the following section, I provide the empirical model estimation strategy employed to answer the research questions posited at the introductory part of the essay.

1.4   Econometric model and estimation strategy

In order to estimate the impacts of creative class and HC on regional economy (GDP growth, employment growth, and wage[7] growth) and compare the results, as well as analyze other creative class impacts of BOH, I employ a dynamic panel growth model that has the following form (Arellano, 2003; Baltagi, 2013)

$$\Delta \ln y_{i\,t} = (\beta_1 - 1)\ln y_{i\,t-1} + \beta_2 \ln x'_{i\,t} + \ln \omega_i + \ln \varepsilon_{i\,t} \quad i = 1,...,N \,\&\, t = 2 \quad (1.1)$$

Where $\Delta \ln y_{i\,t}$ is regional economic performance in logs difference over 11 years measured by real GDP, employment, or wage in region i in year t, $y_{i\,t-1}$ is economic performance of a region in the previous year (the lagged dependent variable), β_1 is coefficient of the lagged dependent variable, $x'_{i\,t}$ are sets of share of creative class or HC in region i and year t, β_2 is coefficient of share of creative class or HC, ω_i is time-invariant component of the error term, and $\varepsilon_{i\,t}$ is time-variant component of the error term. Put differently, ω_i is an unobserved, region-specific, time-invariant effect, which may be correlated with variables of $x'_{i\,t}$ but not with $\varepsilon_{i,t}$, and $\varepsilon_{i,t}$ is an independent and identically distributed (iid) error or idiosyncratic term with $E(\varepsilon_{it}\,x'_{it}) = 0$ for all i and t.

The above equation represents a growth function and can equivalently be written as:

$$\ln y_{i\,t} = \beta_1 \ln y_{i\,t-1} + \beta_2 \ln x'_{i\,t} + \ln \omega_i + \ln \varepsilon_{i\,t}, i = 1,...,N \ \& \ t = 2,...,T \ (1.2)$$

When the all the necessary variables of the study are included; equation (1.2) can be rewritten into the following estimable model:

$$\ln y_{i\,t} = \beta_1 y_{i\,t-1} + \beta_2 \ln x'_{i\,t} + \beta_3 \ln k'_{i\,t} + \beta_4 \ln yr^*_{i\,t} + \ln \omega_i + \ln \varepsilon_{i\,t}\ i = 1,...,N \& t = 2,...,T \ (1.3)$$

Where $k'_{i\,t}$ is set of control variables in region i and year t, β_3 is coefficient of control variables, $yr*$ is year dummy included to control unobservable shocks, and β_4 is coefficient of year. The potential problem that arises in using the above model is that the lagged dependent variable, regional economic performance, will be correlated with the time-invariant region fixed effect error terms ω_i, which in turn will lead $y_{i\,t}$ to correlate with ω_i. This inflates the coefficient of lagged dependent variable and, hence, results in upward panel bias (Hsiao, 1986), which eventually will lead to endogeneity problems and instability of the estimation. This phenomenon will manifest pooled OLS upward panel bias, resulting in an inconsistent estimation. One way to reduce upward bias is to employ within (fixed effects, or FE) technique. However, the problem of the within estimator is that the sum of the parame-

ters of lagged dependent variables has a tendency toward downward panel bias (Nickell, 1981), even if these variables are not serially correlated with ε_{it}. If the spell of $T \to \infty$, then the downward bias of the within estimator will be minimized; yet, evidence shows that even for T = 30, FE estimator has a downward bias.

The panel bias will be captured by introducing the first difference. When this is applied to equation (1.3), the following will be obtained:

$$\Delta \ln y_{it} = \beta_1 \Delta \ln y_{it-1} + \beta_2 \Delta \ln x'_{it} + \beta_3 \Delta \ln k'_{it} + \beta_4 \Delta \ln yr'_{it} + \Delta \varepsilon_{it} \quad i = 1,...,N \ \& \ t = 3 \ (1.4)$$

Now the fixed-effects error term has been purged. Substituting the general economic performance growth equation (1.4) by a more specific regional economic performance indicator such as real GDP growth, the following estimable growth model can be derived:

$$\Delta \ln GDP_{it} + \beta_1 \Delta \ln GDP_{it-1} + \beta_2 \Delta \ln x'_{it} + \beta_3 \Delta \ln k'_{it} + \beta_4 \Delta \ln yr_{it}^* + \Delta \ln \varepsilon_{it}$$
$$i = 1,...N, \ \& \ t = 3,...,N \qquad\qquad (1.5)$$

Where *GDP* refers to the gross domestic product of an administrative region in Germany with the assumption that

$$E(GDP_{it} \ \varepsilon_{it}) = 0 \ for \ i = 1,..,N \ t = 3,...,T$$

The estimation procedures for employment growth and wage growth, as well as for growth of other creative class (OCC), follow the same approach. However, in order not to duplicate the approach I do not include estimations for these variables.

Now, because the time-invariant variable (ω_i) is kicked out, the estimation is supposed to be free from at least the upward and downward bias effects (Ahn and Schmidt, 1995) allowing us to further use the two advanced GMM estimators. These are difference GMM (DGMM) estimator (Anderson & Hsiao, 1981; M. Arellano & Bond, 1991; Holtz-Eakin, Newey, & Rosen, 1988) and SGMM estimator (Arellano and Bover, 1995; Blundell and Bond, 1998), each having two forms. DGMM has, for example, one-step difference GMM and two-step difference GMM. Similarly, SGMM has one-step and two-step SGMM. The use of DGMM estimator suffers from large finite sample bias when available instruments are weak. In case of persistent series (value of autoregressive order, β_1, is close to unity) and the variance of the fixed effect (ω_i) in-

creases relative to variance of disturbances (ε_{it}), instruments (lagged values of variables for subsequent first differences) are weak (Trufat, 2006).

The simulation of Blundell and Bond (1998) and Blundell, Griffith, and Windmeijer (2002) showed that DGMM estimator, in a situation with weak instruments, is biased downward to within group estimator. The bias can be detected by comparing first-differenced GMM results of autoregressive parameter with that of OLS and within estimator. Consistent estimate of GMM exists in the absence of finite sample biases if estimation lies between OLS and within estimators (Nickell, 1981). Persistence of sample biases can be detected by looking at the coefficient in which the closer β is to unity, the more likely that bias exists due to weak instruments. Furthermore, because first difference uses deep lagged values of dependent variable to instrument dependent variable, this works at a cost of reducing sample size. This problem will be enormous if unbalanced data are used.

Under such conditions, SGMM works well because it subtracts averages of future values instead of lags. Indeed, SGMM (Arellano and Bover, 1995; Blundell and Bond, 1998; Hsiao, 2003) reduces the problem of finite sample biases associated with weak instruments and estimates a system of equations both in first differences and in levels. In the first-difference equations, *lagged level values* of the variables are used as instruments whereas in levels equations, *lagged differences* are used as instruments. This estimation strategy requires additional $T-3$ moment conditions to be valid: $E[\Delta \ln \varepsilon_{i,t-1}(\varepsilon_{i,t} + \omega_i)] = 0$ *for* $t = 4,\ 5,...,T$. These moment conditions can only be fulfilled when the change of GDP is not correlated with region-specifics ω_i or with the epsilon of the next period (a region doesn't have knowledge of future shocks).

The implementation of DGMM or SGMM depends on which better fulfils the requirements of serial correlations and over-identification. Whereas the Arellano-Bond AR (1) and AR (2) test identifies the existence of serial correlation, Sargan or Hansen test informs existence or absence of over-identification. The GMM estimator is consistent if there is no second-order AR (2) serial correlation in the error terms of first-difference equation. The null hypothesis that errors are serially uncorrelated is tested against the alternative; and not rejecting the null hypothesis shows the validity of the assumption of no second-order serial correlation. The Sargan or Hansen diagnosis, therefore, informs whether sets

of instruments used are properly identified and valid. The set of instruments used are valid if there is no correlation between instruments used and error terms. The null hypothesis that instruments and error terms are independent is tested against an alternative, and failure to reject the null hypothesis suggests that the instruments used are valid. The choice of Sargan or Hansen differs in the use or non-use of the robust option. If robust option is used the Hansen test can be used. In this study, I use SGMM estimator because I have found the results to be unbiased and consistent. In the following section, I provide description of the data.

1.5 Data and descriptive statistics

This study uses 11 years (1998–2008) balanced administrative panel data drawn from the Sample of Integrated Labor Market Biographies IAB (SIAB 1975–2008) of the Institute for Employment Research (IAB) as well as from the Federal Statistical Office of Germany. Data from IAB contain an individual panel, establishment panel, and establishment history panel. The individual panel contains employment histories of 1.6 million employees who are subject to paying social security—a 2% sample of employees over 1975–2008. All data on employment are from public and private organizations. The sample, which has more than 200,000 employments per year, provides information on daily wages, working days, and further individual characteristics for all employees who contribute to the social security system. Among the excluded are self-employed, civil servants, part-time workers, and apprentices. Because the study is based on annual data, I use all full-time employees on June 30 of each year. In addition to detailed information on professions, the data contain personal characteristics of workers, including gender, age, and education, as well as basic information about the employer (industry affiliation, location, and firm size). There are 132 profession/occupation categories, each with a three-digit code ranging from 011 to 996. An advantage of this sample is the inclusion of the regional professional composition of employed persons. Further advantages include the high validity and up-to-date nature of the data (Windmeijer, 2005).

Using the framework of creative class classification made earlier in this essay creative class is categorized into CC, CP, and BOH (Appendix A1). The IAB database CC includes experts who work in hard sciences, engineering, technology, teaching, and research centers. These are indi-

viduals registered in the employment database as physicists, biologists, chemists, mathematicians, statisticians, geologists, computer experts, engineers, architects, faculty members, teachers, researchers, think tank workers, and information experts. The second groups of employees, CP, are identified as economists, health professionals, business analysts, juries, public service administrative workers, managers, senior officials, politicians, legislators, senior officials, business professionals, police inspectors, detectives, sociologists, and anthropologists. Furthermore, I use the approach of Boschma and Fritsch (2009) as well as Möller and Tubadji (2009) who took BOH as a separate groups of creative class. These experts are archived in the database as creative writers, performing artists, photographers and image and sound recording equipment operators, entertainers, sports associate professionals, and fashion and other models (construction of the creative class is presented in Appendix A1).

Further, data on HC which is measured by educational attainment is aggregated into three (detail Table 1.2). I also use establishment panel data, which contain information on median wage, industry classification and workplace—a crucial database on which I base the whole analysis of this essay. Moreover, data on regional GDP and consumer price index (CPI) are obtained from the Federal Statistical Office of Germany, where nominal GDP is converted into real GDP using GDP deflator. Further, data on population, region area, and location of industry (as in East or West Germany) are obtained from establishment panel history (BHP). Observations with no valid information for the analysis are dropped. For some regions, such as Chemnitz and Leipzig, I could not find valid data due to either being merged with other regions or have recently become administrative region. These regions were dropped, thus reducing the number of regions for the study to become 394, which is 95% of the total number of regions (NUTS3) in the country. Thus, the sample of the study is almost fully representative.

The data reveal that 12% of the creative class in Germany comprises the CC, which perfectly matches up with Florida's (2002) observation. He identified that the share of the creative core comprises 12% of all the labor force in the United States. However, his empirical evidence that about 40% of the labor force in the United States is creative class (aggregate of CC and CP) is not congruent to the present study result, where the share of CP alone is 55% (Table 1.3), well over the sum of CC and CP of the United States. The share of BOH is the smallest—only 7% of

total full-time employees. The fact that BOH are highly mobile, work privately, and are usually not recorded as employees in the employment database would cause their share to be less represented than one might expect. Still, the 7% figure is believed to good figure.

The combined share of CC and CP in a given region appears to be 67% (12% CC + 55% CP) a share nearly two times that of the United States. It should, however, be taken into account that if the share of the CC and CP (67%) were taken from the total labor force, instead of from only the full-time employees, the share would have been significantly lower than 67%. It is also noted that the proportion of the primary, intermediate, lower secondary, and upper secondary school graduates without vocational training (EDU1) is 12%; share of employees with primary, intermediate, lower secondary, and upper secondary school graduates with vocational certificates (EDU2) is 48%; and the share of employees with applied university graduate and non-applied university graduates (EDU3) is 13% of total full-time employees. It is possible to understand from these figures that the share of employees with vocational certificates (nearly half of the sample) is driven by a peculiar feature of Germany's education system that places great emphasis on practical training. In fact In Germany a primary, lower secondary or upper secondary school graduate without vocational training can hardly get a job. And even if someone gets a job with such a profile, the job would most likely be low-paying and on a temporary basis (Table 1.3).

Table 1.3
Share of creative class and human capital (obs. = 4334)

Variable	Mean	Std. Dev.	Min	Max
CC	.123	.098	.001	.711
CP	.545	.385	.002	.761
BOH	.078	.081	.001	.620
EDU1	.117	.107	.002	.789
EDU2	.483	.343	.002	.946
EDU3	.130	.100	.001	.717

There is strong evidence that the presence of a large share of tertiary-level graduates in a region is likely to imply the presence of a large of share of creative class because a creative or innovative individual is most often than not someone with high level of education (Glaeser, 2005). I find that the correlation between creative class and HC is strong and that the association among the six variables (three of them creative class and the other three HC indicators) is positive and strong, with all the correlation levels being more than 0.8 (Table 1.4). The details indicate that the level of association between CC and EDU1 appears to be 0.935; between CC and EDU2, 0.905; and between CC and EDU3, 0.931. Similarly, I have found that the association between CP and EDU1 is 0.904, between CP and EDU2, 0.996; and between CP and EDU3, 0.889. Moreover, there is a strong relationship between BOH and EDU1 (0.951), BOH and EDU2 (0.876), and BOH and EDU3 (0.897). Such strong positive correlations between the creative class and HC seem to prove that creative class and HC may merely indicate a name difference. Yet, it is not possible to prove this through correlation unless further rigorous analysis is done—and that is the next part of the discussion.

Table 1.4
Correlation between creative class and human capital

Variable	CC	CP	BOH	HC1	HC2	HC3
CC	1					
CP	0.901*	1				
BOH	0.958*	0.875*	1			
EDU1	0.935*	0.904*	0.951*	1		
EDU2	0.905*	0.996*	0.876*	0.896*	1	
EDU3	0.931*	0.889*	0.897*	0.834*	0.873*	1

1.6   Estimation results and discussion

In this section, the estimated econometric results of regional economic performance and other creative class are presented. The report is presented in four growth models: real GDP, employment, wage, and creative class. All results of the first three models are discussed thoroughly in order to provide evidence on whether the estimation made based on the

panel data described under section 5 can corroborate or falsify (Florida, 2002) thesis that creative class is superior to HC in explaining regional economy. Furthermore, I will interpret the results of the last model, which aims at testing Florida's theory that art experts attract other creative class (CC and CP).

1.6.1 Creative class, human capital and regional economy

In this section, the results of the three models—GDP growth, employment growth, and wage growth—will be presented. Each model has two components, the creative class and the HC, as explanatories; and for each model a standard approach, that is, autoregressive estimation technique, is used to determine the maximum lag length of dependent variables. The rule of thumb in using this technique is to take as many lag lengths as possible, provided the lags have robust effects on the dependent variable. However, the use of more lags substantially reduces the number of the observations. The autoregressive estimation shows that in the GDP growth model, three lags of the dependent variables have a significant impact on growth of GDP. In the employment growth model, its two lags have robust effects on employment growth. Similarly, in the wage growth model, the first two lags of the dependent variable have significant effects on wage growth (Appendix A2). Therefore, while three lags are taken for the GDP growth model, I take two lags for the employment and wage growth models. All three models are estimated using the command xtabond2,[8] a statistical software syntax developed by Roodman (2009). Following lag length determination of the dependent variables in each of the three models, specification tests were made using consistency and efficiency criteria to check the fitness of the model.

In doing so, I tested DGMM estimator for the GDP, employment, and wage growth models, but it failed to be a good estimator for all. In fact, the tests showed that the sum of the coefficients of the lagged dependent variables in each of the GDP, employment, and wage growth models showed either unit root process, estimation being biased upward (Hsiao, 1986) or being downward biased (Nickell, 1981). In fact, Blundell et al. (2002) and Blundell and Bond (1998), using Monte Carlo experiments, showed that the coefficients for the lagged dependent variable were strongly biased downward in DGMM model in case of near unit root processes. The present study fits with the observation made by these scholars and therefore excluded DGMM.

A further test using the SGMM estimator is found to be appropriate for the GDP, employment, and wage growth models. For the GDP model, the two-step SGMM fulfils consistency requirement as the sum of the coefficients of the lagged dependent variable lies between the pooled OLS and within estimators. To be sure, the sum of the coefficients of the lagged dependent variables GDP is 0.981 in the pooled OLS, 0.335 in the FE, and 0.885 in the two-step SGMM when creative class is used as explanatory variable. In the same manner, when HC is used as an independent variable, the sum of the coefficients of the lagged dependent variable GDP is found to be 0.976 in the pooled OLS, 0.335 in the FE, and 0.937 in the two-step SGMM (Appendix A2).

In the employment growth model, two varieties of the SGMM are found to be appropriate: the first-step SGMM for the creative class–driven employment growth model, and the two-step SGMM for the HC-driven employment growth model. In the creative class–driven employment growth model, a test of the consistency of the one-step SGMM shows that the sum of the coefficients of the lagged of employment is 0.900; it is 0.945 in pooled OLS and 0.385 in the within estimator, where 0.900 lies between OLS and FE. Similarly, in the HC-driven employment growth model, the sum of the coefficients of the lagged dependent variable employment has 0.930 lying between the coefficients in pooled OLS, which is 0.950, and FE estimator, which is 0.407 (Appendix A2).

By the same token, in the wage growth model, the two-step SGMM estimator is found to be appropriate because the sum of the coefficients of the lagged dependent variable in two-step SGMM, which is 0.918, lies between the aggregate of the coefficients of the lagged dependent variable in pooled OLS with 0.949 and in the FE estimator with 0.508, when creative class is used as the independent variable. Similar patterns are observed when HC is employed as covariate in which the sum of the coefficients of the lagged dependent variable in the two-step SGMM, which is 0.927, is between 0.954 in pooled OLS and 0.517 in fixed-effects estimator (Appendix A2).

Following lag length determination and dynamic panel model identification, I compare the estimated results of the impacts of creative class and HC on regional GDP, employment, and wage growth (Table 1.5). First, I discuss the impacts of the lagged dependent variables on each dependent variable. Second, the estimation results of the effects of the creative class and human capital on GDP, employment, and wage

growth are presented. Third, the implications of the influences of control variables on regional economic performance are discussed. These variables among others include firm size, population density, and Krugman specialization index. Furthermore, year dummy is included as control variable to control shocks that may not be accounted by region-specific effects (Roodman, 2009).

Analyses of the impacts of the lagged dependent variables on the respective dependent variables show a number of interesting results. In the creative class–driven regional GDP growth model, for example, the results show that the first and second lag of GDP affect its GDP growth positively and significantly at $p < 1\%$. More specifically, a 1% increase in the first lag of GDP is attributed to a 0.81% growth of GDP, and a 1% increase in the second lag of GDP causes current GDP to grow by 0.11%. The first lag of GDP, therefore, has more effect than the second lag as the coefficient of the parameter in the first lag appears to be more than the coefficient of the second lag. Moreover, in the HC-driven GDP growth model, the first and second lags of GDP are found to have robust, positive impacts on growth of regional GDP where a 1% increase in the first and second lag of GDP have induced regional GDP to grow by 0.86% and 0.12%, respectively. The two lags show that they have statistically and economically significant impacts on current GDP growth. The third lag, however, has a negative and significant impact on GDP growth in both the creative class and HC-driven GDP growth models.

In the employment growth model, the first lag of employment appears to have strong, positive feedback on employment growth in both the creative class and HC-driven employment growth models. The effect is not, however, the same in both models, because whereas a 1% increase in the first lag of employment has contributed to a 1.14% growth of employment when the creative class is used as regressor, the same amount of increase (1% rise in the first lag of employment) has resulted in a 0.88% current employment growth when human capital is included as explanatory variable. Moreover, it is interesting to observe a difference in the directions and magnitudes of the employment growth impact of the second lag of employment when creative class and HC are used as explanatory variables. More specifically, it is found that although the second lag of employment has a negative and significant effect on growth of current employment when creative class is included as explanatory variable, the effect of the second lag of employment on contemporary em-

ployment growth is positive but not robust when human capital is taken as the regressor. The difference could indicate that the share of the creative class may contribute to positive employment growth only when creative class is used as covariates—or just in the next year. After that, creative class individuals may be not as productive as in their first-time employment or just in the following year to have positive impact and consequently may discourage growth of employment in two years. It may also be possible that persistence of previous-year employment impact on growth of employment may be negative when the variable creative class is used as an explanatory variable.

With respect to the implications of the lagged dependent variable wage, the estimation reveals that the first and second lags of wage have positive and strong effects on current wage growth in both the creative class and HC-based regional wage growth model. Indeed, past-year wage status of a region has a considerable impact on the growth of a region's wages, making the extent of the impact robust at less than 1% when creative class as well as HC variables is used as determinants of wage growth. An important observation from the result is that the elasticity of wage growth, with respect to its first and second lags, is almost same when creative class and HC are used as covariates. That is, when the creative class is used as the explanatory variable, the responsiveness of wage growth with respect to its first and second lag growths are 0.673 and 0.245. When HC (instead of creative class) is used as regressor, the elasticity of wage growth in response to its first and second lags are 0.685 and 0.242. This may indicate that creative class and HC might have similar influences on wage when previous-year numbers are employed.

The above discussions highlight the effects of the lagged dependent variables on GDP, employment, and wage growth. Below, I provide the estimated results of the effects of creative class and HC on regional economic performance (GDP, employment, and wage). The results support Florida's (2002) theory that the creative class plays a critical role in regional economic growth through GDP, employment, and wage growth. Specifically, I find that a 1% increase in the share of the CC is followed by a 0.58% increase in the growth of regional GDP. The same is true for creative professionals where a 1% increase in the share of creative professionals has contributed to regional GDP growth by about 0.23%. One can, however, observe that though the regional GDP growth effects of the share of CC and CP are found to be robust at 1% level, it is the CC

that plays a bigger economic impact (the elasticity of real GDP growth with respect to CC is more than with respect to CP). The creative class theory identifies CC and CP as university graduates for whom the CC work in areas of hard science, engineering, research, and teaching activities whereas the CP are engaged in other occupations as associate innovators. Because science and related areas happen to be of high significance for innovation, the estimation result that the creative core is superior to creative professionals in explaining regional GDP growth corroborates Florida (2002) contribution.

The creative class has also contributed immense for employment. Indeed, the share of the CC and CP boosts employment at $p < 1\%$ level. One might explain that because the CC are engaged in scientific, engineering, research, and teaching activities—and all such works tend to provide new ideas, innovations, and technology—these activities will have a reinforcing effect on increasing output and productivity of a region. The increase in output of a region tends to scale up the likelihood of demand for, and supply of, labor. When the labor market is able to take up a significant share of the labor force, there is a natural tendency to increase employment. The same applies to the case of creative professionals where the presence of innovative labor force—whom Florida considered to be problem solvers and generators of new ideas—tends to increase the competency of knowledge economy as well as competitiveness of a region. A region with a well-functioning knowledge economy provides a tick labor market—a market resilient to shocks where the employment conditions tend to increase sustainably. Therefore, the thesis that creative class plays huge role in harnessing the economy of a region through employment is supported by the present empirical evidence. However, if one would compare the magnitude of the impact by CC and CP, still, the former has a greater effect. Moreover, the share of creative core and creative professionals are found to have positive effects on wage growth. Nevertheless, although the level of impact by the CC is robust at $p < 1\%$ the influence of the share of CP on wage growth is not robust. However, contrary to the theoretical contribution of Florida and the empirical insights of Boschma and Fritsch (2009), the influences of the share of BOH on regional GDP, employment, and wage growth have consistently negative and significant impacts. One may infer that professions of culture, promotions, music, film, designs, and the like have discouraging effects on economic performance.

Human capital-like creative class appears to have different impacts on regional economic performance. Put differently, human capital has different influences on GDP, employment, and wage growth. The impact of EDU3 (share of university of applied science and university graduates) has a positive impact on GDP and employment growth of a region, with the level of impact being robust at 1% level. This result is consistent with the studies of Mincer (1958), Hall (1975), Fabricant (1959), Becker (1960b; 1962; 1993), and Schultz (1963), who identified tertiary education as having strong influence on GDP growth. The elasticity of regional GDP growth with respect to EDU3 is found to be large enough in that a 1% increase in the share of university graduates increases performance of GDP growth by 1.28%. This effect is more than what the creative core or creative professional have impacted GDP. The result further shows that the shares of university graduates, creative core, and creative professionals all have significant impacts on the growth of employment, though the elasticity of employment growth with respect to the growth of the share of tertiary-level graduates, CC, and CP differ. Indeed, the creative core is found to be superior to creative professional and university graduates as the *beta* of creative core is more than the beta of creative professionals and university graduates.

In the same manner as the share of EDU3, the influence of EDU2 (the share of lower, junior, and secondary school graduates with vocational training) has not only positive but also substantial effects on regional GDP growth, thus confirming the importance of vocational training. In particular, I obtained that a 1% increase in the growth of the share of EDU2 leads to a 0.18 % growth in regional GDP over the years 1998–2008. However, the share of EDU2 doesn't have noteworthy effects on employment growth and has even contributed negatively to wage growth. Moreover, the share of employees without vocational trainings (EDU1) has a consistently negative impact on GDP, employment, and wage growth. The effect is profound on employment and wage growth but not on GDP growth. Indeed, in Germany it used to be the case that a graduate with neither vocational training nor university qualification would have hard time in getting a job. Even if employed, it would be in a low-paying job on a temporary basis. It would not, therefore, be a surprise to have observed a negative GDP, employment, and wage growth impacts of non-university graduates who have no vocational certificate. Specifically, the negative effect on employment growth is

found to be robust at the 1% level. This implies that the presence of a large share of these groups of people in a particular region would retard the economic performance of a region, because these people do not have the knowledge and capability to generate new ideas, to innovate, and to provide options that solve socioeconomic problems.

In this case, the theory that creative class is superior to HC in driving regional economic growth appears to be not supported. It is, indeed, evident that the growth of the share of the CC and CP each has a positive and robust effect on GDP growth at $p < 0.01\%$. Similarly, the HC, which refers to tertiary level graduates (HC3), has a strong, positive effect on the growth of regional GDP at $p < 0.01\%$. However, a comparison of the effects of the growth of university graduates (EDU3) with CC and CP growth shows that it is, indeed, the EDU3 that has a greater economic impact as the elasticity of GDP growth with respect to HC3 is more than what the GDP growth responds to the CC or the CP. It is, therefore, possible to conclude that the creative class approach as praised by Florida (2002) could be taken as an alternative method in analyzing regional economy; the impacts are found to be impressive, but the thesis that the creative class is superior to the conventional HC in generating regional economic growth is rejected, at least in the context of Germany.

Apart from the lagged dependent, creative class, and HC variables, I use some variables as controls for all the three growth models. For the GDP growth model, I use employment and firm size as controls; for the employment growth model wage, I employ years of work experience, firm size, and population density; and for the wage growth model, work experience, employment, firm size, and Krugman specialization index (KSI) are used. The reason for the inclusion of wage as control variable emanates from the observation that some regions with better minimum wage tends to have good labor markets and employment conditions because these regions are *a priori* rich and are able to hire a good number of employees. On the contrary, poor regions with low wages will have a discouraging effect on employment growth because naturally people would prefer to be employed in regions where wages are better. Moreover, work experience is included as control with the expectation that having experience tends to encourage employment growth, as the more individuals have proven experience, the greater the likelihood of being hired; this is because experienced employees are presumed to have greater productivity.

The estimation reveals that the variable employment and industry size contribute immense to regional GDP growth. An increase in the number of the employed labor force tends to boost creative class–driven GDP growth by about 0.11% and the HC-driven GDP growth by 0.02%. The result implies that an increase in employment is followed by a higher level of productivity growth. Growth of firm size also has a much higher effect on regional productivity to have a robust impact on regional growth. On the contrary, the effect of population density has a strong negative impact on GDP growth. This is consistent with the Malthusian economic theory that an increase in population density discourages economic growth if aggregate population growth emanates from the growth of an inactive labor force, particularly the young and old (Malthus, 1798).

Also, some useful insights are observed with respect to the implications of controls on employment growth. Contrary to expectation, wage as a control variable has a negative impact on employment growth in the creative class–driven employment growth model. This result, though not significant, is consistent with the theory that an increase in wage level should be reflected in a decrease in employment (Even and Macpherson, 2003; Flinn, 2010; Flinn, 2006). The theory argues that if more labor force is employed, wages should go down in order to recruit as many employees as possible. However, such a theory does not appear to be correct when HC-driven employment impact of wage is considered. This is because wage appears to have a positive and significant impact on employment at 1% level rejecting the classical view that wage and employment goes in opposite directions. Moreover, mean year experience of an employee has a positive influence on employment growth when creative class and HC are used as covariates. However, though the influence is significant at 1% level when HC is used as covariate, the effect is not robust when creative class is employed as explanatory variable. Moreover, it is found that firm size has a negative and robust impact on employment growth when creative class is used and a positive and insignificant effect when human capital is employed. Population density, on the other hand, has a discouraging and significant effect on employment in the HC-driven employment growth model but has a positive and robust impact in the creative class–based employment growth model.

The result further reveals that mean years of experience and employment have considerable impacts on wage growth at $p < 1\%$ and $p < 5\%$ respectively when creative class is included as regressor; nevertheless,

when human capital is used, there is no substantial impact of experience and employment on wage growth. The growth in the population density of a region—regardless of the quality of the population—has a positive and significant impact on wage growth, which seems to be contrary to what one might expect by intuition(Blanchflower and Oswald, 1994). One might normally anticipate that an increase in population density of a region would put pressure on employment and, therefore, on wage, which eventually could affect wage growth in a negative manner. However, this does not appear to be the case for at least two reasons. A first possibility is that if an increase in the population density is attributed to a rise in the number of highly skilled people, the effects of population density on wage growth would still be positive. A second possibility is that when a region is already rich and is capable of employing more and more people with good remuneration, population density may still tend to increase wage growth instead of becoming a constraint of wage.

The wage growth implications of the control variables in both the creative class and HC-driven model wage models are also noteworthy. It appears that the influence of regional specialization on wage growth varies in cases of creative class and HC-driven wage growth models. Regional specialization, also called Krugman specialization index (KSI), measures the level of industry specialization at a regional level with respect to the level of industry specialization at the national level. The index ranges from a minimum of 0, when there is no difference between regional and national-level specializations of industries, to 2, when there is extreme specialization at the regional level. The estimation shows that the more the region is specialized, the more negative the impact it has on growth of regional wage in both the creative class and HC-driven model of wage growth. In particular, in the creative class–based wage growth model, the effect of regional specialization appeared to be not only negative but substantially so, at the 5% level. This has important implications in regional economic policy analysis because industry specialization, which is a function of the share of the number of employees in an industry in a region from total number of employees of industries at national level, can have not only short-run but also long-run implications on the competitiveness of regions.

To sum up, the above analysis has shown a number of interesting results on the impacts of creative class and HC on the economic performance of administrative regions in Germany. It has attempted to identify

whether the creative class or the conventional HC better drives economic growth. Such analysis is based on the SGMM estimator that takes care of omitted variables, measurement errors, and endogeneity. The analysis in each of the GDP, employment, and wage growth models is based on the properly specified SGMM model. For the GDP growth model, for example, I have shown that the two-step SGMM model is consistent and unbiased as its sum of the coefficients of the lags lies between pooled OLS and within estimator. Further, a test of the specification of the regional GDP growth model using the Arellano-Bond test of first order AR (1) and second order AR (2) shows that error terms are not serially correlated and that there is no endogeneity problem. This is proved by the results in which in the first order AR (1) has $p = 0.000$, which is far less than the threshold of $p < 0.05$; and in the second order of the Arellano-Bond AR (2), $p = 0.289$ when creative class is used. When HC is used as explanatory variable, the first order AR (1) has $p = 0.000$ and the second order has p = 0.943; both are within the required value. These results show that the time-variant variables are serially uncorrelated. Besides, the Hansen over-identification test of $p = 0.347$ when creative class is used as explanatory variable and $p = 0.193$ when HC is used as regressor shows that the number of instruments used in the GDP growth model are not over-identified and, therefore, are valid.

A similar serial correlation and instrument over-identification test has been run for the employment growth model. It is known that $\text{cov}(\Delta\varepsilon_{it}, \Delta\varepsilon_{i,t-k}) = 0$ for $K = 1, 2, 3$ is rejected at a level of 0.05 if $p < 0.05$. If $\Delta\varepsilon_{i,t}$ are serially uncorrelated, we expect to reject at order 1 that the time-variant error terms are autocorrected (Cameron and Trivedi, 2010). This is indeed the case in the estimation of employment growth where the result rejects presence of error terms serial correlation at first order AR (1) because $p = 0.000$. At the second order, AR (2) $\Delta\varepsilon_{it}$ and $\Delta\varepsilon_{i,t-2}$ are found to be serially uncorrelated; I find $p = 0.587$ when creative class is used as covariates and $p = 0.062$ when HC is used as the driver of employment. In both cases, $p > 0.05$. Moreover, the Hansen over-identification test of $p = 0.447$ when the creative class is used and $p = 0.984$ when HC is used shows that the number of variables used as instruments are not over-identified because the values $p > 0.05$ show absence of over-identification. Overall, the one-step SGMM creative class and two-step SGMM HC-driven employment growth models show that

the estimation is consistent, has no serial correlation of error terms, and has no over-identification problems of instrumental variables (Table 1.5). The wage growth model has also shown similar estimation in that the time-variant or idiosyncratic error terms are not serially correlated and that the instrumental variables used are not over-identified.

Table 1.5
Two-step SGMM estimates for regional GDP, employment and wage

Explanatories	GDP growth		Employment growth		Wage growth	
	Creative class	Education	Creative class	Education	Creative class	Education
	β (Std. Err)	β (Std. Err)	β (Std. Err)	β (Std. Err)	β (Std. Err)	β (Std. Err)
Lag1 GDP	.814 (.040)***	.863 (.029)***				
Lag2 GDP	.119 (.033)***	.124 (.031)***				
Lag3 GDP	-.048 (.028)*	-.055 (.022)**				
CC	.578 (.158)***	-.012 (.017)	2.109 (.547)***		.140 (.032)***	
CP	.230 (.066)***	.185 (.054)***	.198 (.064)***		.002 (.009)	
BOH	-.942 (.232)***	1.282 (.137)***	-3.183 (.68)***		-.161 (.04)***	
Educ1		-.012 (.017)		-379 (.070)***		-.015 (.007)**
Educ2		.185 (.054)***		.254 (.168)		-.025 (.022)
Educ3		1.282 (.137)***		.343 (.155)**		.054 (.023)**
Lnempt.	.116 (.030)***	.018 (.004)***			. 008 (.003)**	
Ln Industry size	.082 (.041)**	.114 (.019)***				
Ln Density	-.150 (.039)***	-.193 (.049)**				
Lag1 employment			1.102 (.036)***	.881 (.036)***		.001 (.002)
Lag2 employment			-.140 (.03)***	.055 (.037)		
Ln wage			-.045 (.088)	.435 (.101)***		
Lag1 wage					.673 (.030)***	.685 (.031)***
Lag 2 wage					.245 (.025)***	.242 (.027)***
Ln experience			.123 (.042)***	.073 (.046)	.026 (.007)***	.038 (.008)***
Ln industry			-.065 (.02)***	.037 (.018)**	-.004 (.003)	.001 (.003)
Ln density			.0786 (.044)*	-791 (.150)***	.018 (.005)***	.011 (.005)**
KSI					-.025 (.005)**	-.011 (.009)
Year dummies	included	included	included	included	included	included
AR (1)	t=-9.08 Pr>t=0.000	t=-9.71 Pr>t=0.000	t=-5.74 Pr>t= 0.000	t=-4.88 Pr>t=0.000	t=-8.61 Pr>t=0.000	t=-8.48 Pr>t=0.000
AR (2)	t=-1.06 Pr>t=0.289	t=-0.07 Pr>t=0.943	t= -0.54 Pr>t= 0.587	t=-1.85 Pr>t= 0.062	t=-1.88 Pr>t=0.060	t=-1.74 Pr>t=0.082
Hansen overident.	χ^2(24)=26.12 Pr >χ^2=.347	χ^2(16)=20.65 Pr >χ^2=0.193	χ^2(8)=7.87 Pr>χ^2=0.447	χ^2(45)=27.04 Pr >χ^2=0.984	χ^2(45)=37.74 Pr >χ^2=0.770	χ^2(45)= 49.41 Pr >χ^2=0.301
Observations	3,152	3,152	3,152	3,546	3,546	3,546
Regions	394	394	394	394	394	394

Standard errors in parentheses, *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

1.6.2 Art experts and other creative class

Florida (2002) argued that other creative class, sum of CC and CP, flock to places where BOH live. He explained that BOH have talents that make them attract other creative class. The present study aims to test whether BOH can attract other creative class and, therefore, attempts to analyze the impact of BOH on other creative class. Furthermore, because the share of creative class in a region can certainly be explained by factors other than BOH, I include employment, GDP growth, firm size, and population density as control variables.

As a stylized approach, the lag length of the dependent variable "other creative class" is determined using autoregressive estimation, showing the first two lags of the share of other creative class having robust impacts on its current growth. Beyond the second lag, the effect is found to be insignificant; therefore, only two lags are taken for the analysis. Following this I found the one-step forward orthogonal or SGMM model as appropriate for the data. This model is suitable because the sum of its coefficients of the lagged dependent variables of other creative class, which is 0.654, lies between the coefficients of pooled OLS (which is 0.903) and of the within estimator (which is 0.409)—a requirement for consistent and efficient estimation in dynamic panel (Appendix A3).

Indeed, estimation results show that the first lag of the share of other creative class (OCC) has positive and substantial impact on the growth of the share of other creative class (Table 1.6). In particular, a 1% rise in the share of the first lag of CC and CP appears to increase growth of creative class by about 0.64 %. The second lag, however, has a negative effect on other creative class with the level of impact being robust at 10% level. Further, the effects of the share of Bohemians on the growth of other creative class are found to be positive and robust at 1% level. This supports Florida's (2002) creative class theory that BOH attract other creative class.

Table 1.6
One-step SGMM estimates for regional creative class growth

Explanatories	β (Stan. Err)
Lag 1 creative class	.644 (.085)***
Lag 2 creative class	-.010 (.017)
Art experts	.981 (.281)***
Lnemployees	.494 (.097)***
Ln GDP	.084 (.041)**
Lnindustry	.019 (.078)
Lndensity	.143 (.221)
Year dummy	included
Arellano-Bond test AR (1)	t = -3.53 Pr > t = 0.000
Arellano-Bond test AR (2)	t = -0.53 Pr > t = 0.593
Hansen over-identification.	x^2 (36) = 42.76 Pr > x^2 = 0.204
Observations	3,546
Regions	394

Standard errors in parentheses, **$p < 0.05$, ***$p < 0.01$

The result is, further, consistent with the contribution of Boschma and Fritsch (2009), who identified that BOH have a positive influence on the geography of other creative people. A high proportion of BOH tend to indicate a dense local culture, lifestyle, and set of values that are different from those of the mainstream labor force. BOH, being artistically creative, could add a sense of liveliness to a location as well as openness to different lifestyles and values, which would then make the region attractive to creative class. Nevertheless, the current result is at odds with the contributions of Möller and Tubadji (2009), who found that the influence of BOH on creative class is not significant. However, their estimation was limited to West Germany for 323 regions with periods spanning from 1975 to 2004 by collapsing the 30 years' data into six panels.

All controls—employment, GDP, firm size, and population density—have positive effects on the share of other creative class. Employment with good payment has a natural tendency to attract a significant share of creative class—employment is, after all, a major part of life and this

without employment is difficult. A 1% rise in employment, keeping all other things constant, increases the corresponding region's share of other creative class by 0.50%. Similarly, I find that that region with commendable GDP records attract a considerable number of other creative class because such rich regions have the capacity to employ as many innovative people as possible in order to have continuous competency. The elasticity of the share of other creative class with respect to GDP growth is 0.08, a figure less than the elasticity of the growth of other creative class with respect to employment. Overall, the conditions of employment of a region as well as its extent of GDP do affect the distribution of other creative class at the 1% level.

Regarding the specification of other creative class growth model, the estimation reveals that that the Arellano-Bond first order AR (1) test proves that there is no autocorrelation of the idiosyncratic error term as the $p = 0.000$ is well below the required threshold of 0.05. Also, the second order AR (2) $p = 0.593$, which is well above the required $p > 0.05$, also confirms that the estimated model does not have any serial correlation problem—which further indicates absence of endogeneity. Furthermore, the Hansen (robust) test of over-identifications, with $p = 0.204$ (which is greater than 0.05), rejects the null hypothesis that the model is over-identified, and therefore the identified instruments are found to be valid. Overall, the estimated other creative class growth model is properly specified.

1.7   Conclusion

Empirical analysis of the economic performance implications of HC has been established since the 1960s when the theory of human capital was formally acknowledged. Since then, HC, at least in mainstream economics, has been known to be exclusively measured by educational achievement. However, more recently, Florida has underscored that measuring HC through educational achievement and examining its effect on economic growth is not adequate. His argument was that education doesn't, and can't, adequately explain HC; as such, he proposed an HC equivalent but more comprehensive variable creative class, which he measures by occupation. His central contribution lies in the theory that creative class is not only crucial but is superior to HC in driving regional economy.

In the present study, motivated by his insight, I estimate and compare the impact of creative class and HC on the economic performance of administrative regions (NUTS3) in Germany using a dynamic panel model that builds on rich administrative data from the years 1998–2008. I doing so, I proxy the dependent variable of economic performance by growth of GDP, employment growth, and wage growth; whereas the explanatory variables creative class and HC are respectively measured by occupation type and education. Creative class is disaggregated into CC, CP, and BOH; while HC is categorized into EDU1, EDU2, and EDU3.

The estimation reveals that the impact of the share of CC and CP on regional GDP growth is positive and significant at $p < 1\%$, confirming the creative class theory that creative capital plays a vital role in enhancing regional economy through GDP growth. By the same token, regional GDP growth effects of the share of university graduates is also found to be positive and robust at $p < 1\%$, corroborating the conventional HC theory that higher-level education does play a positive role in economic growth. The report clearly indicates that contemporary creative class and conventional HC approaches both have critical roles in harnessing regional economic growth. Nevertheless, Florida's theory that creative class is superior to HC (share of university graduates) in explaining regional GDP growth is not supported, because the elasticity of regional GDP growth with respect to EDU3 is rather greater than that of the elasticity of GDP growth with respect to CC or CP.

On the other hand, although employment growth effects of creative core and creative professional are robust at $p < 0.01$, the impact HC (EDU3) has on employment growth is robust at $p < 0.05$. This validates Florida's thesis that creative class outperforms HC in explicating regional employment growth. Moreover, it is found that the share of the CC and share of university graduates have substantial roles in enhancing growth of regional wage—the presence of scientists, engineers, researchers, and faculty members in a region have a positive effect on increasing wage growth because these people have the power and, in fact, the skill necessary to beef up the economy of a territory and, eventually, the wages of a region. Unlike GDP and employment growth models, neither the creative class nor HC better explains the wage growth effects of the region.

Contrary to Florida's insight, art experts (BOH) have a consistent negative effect on GDP growth, employment growth, and wage growth. Yet, BOH do attract other creative class and, therefore, do influence the

distribution of other creative class in a region. Overall, the empirical evidence of the essay reveals that analysis of regional economy through creative class in place of conventional HC could serve as an innovative approach; yet, creative class, as theorized by Florida, is not superior to HC in generating regional economy. Indeed, even if the growth of the share of CC, CP, and tertiary-level graduates has robust effects on GDP growth, it is by no means the share of tertiary-level graduates that has a far greater impact on GDP growth. The reverse holds for employment growth and is inconclusive for wage growth.

Notes

[1] The location quotient theory was developed in part to offer a slightly more complex model to the variety of analytical tools available to economic base analysts. This technique compares the local economy to a reference economy, in the process attempting to identify specializations in the local economy. The location quotient technique is based upon a calculated ratio between the local economy and the economy of some reference unit. This ratio, called an industry "location quotient" gives this technique its name(Isserman, 1977).

[2] Shift-share analysis has generally been used for describing regional and industrial economic growth and examining the structural effect and regional or industrial competitiveness underlining the changes over time. It has been popular in the fields of regional economic, political economy, marketing, geography, and urban studies (Brown, 1969).

[3] The input-output also the I-O model provides multipliers that can be used to estimate the economy-wide effects that an initial change in economic activity has on a regional economy. The initial change involves a change in final demand such as a new construction project, an increase in government purchases, or an increase in exports (Leontief, 1941).

[4] Creativity is a process that can result in the development of novel and useful ideas or processes by an individual or a group (Shalley, 1995). Creativity is associated with a variety of positive workplace outcomes including innovation and productivity. In fact, some proponents even consider creativity necessary for innovation (Amabile,, Conti, Coon, Lazenby, and Herron, 1996). Numerous researchers have approached creativity from a variety of different perspectives (Amabile, and Conti, 1999; Amabile, et al., 1996; Shalley, 1995). For example, much of the extant literature on creativity explores it both on the individual and firm level. However, more recently Florida (2002) introduces the novel idea of a "creative class." In his 2002 book Rise of the Creative Class, Florida argues that economic growth is in part driven by the generation of new ideas stemming from the combination of knowledge in new ways.

[5]The conventional approach of regional or urban development takes business climate, firms and industries as fundamental drivers and that the presence of favorable institutions (rules and regulations) that foster business undertakings and investment are considered to be critical factors for the growth of regional economy. While such approach is still appreciated by mainstream economists, Florida (2002) takes people climate-which is measured by diversity, tolerance and talent-as a crucial drivers of regional economy. According to this principle region that accommodate different people with heterogeneous culture and ethnicity as well as with high level of tolerance tend to attract a number of innovative people, particularly, the most educated ones. The attraction of the skilled or talented people would, eventually, create opportunity for the region to grow because a region endowed with innovators is likely to get many opportunities.

[6] For details of how occupation can be used as indicators of creative class or HC, readers are invited to reference the works of Markusen et al. (2008).

[7]The three indicators of regional economic development have actually been fundamental variables used in the analysis of economic development in mainstream economics.

[8] The syntax has three parts: the first lists the dependent and explanatory variables; the second part is for gmm style, which lists a set of endogenous and predetermined variables; and a third part is for the ivstyle, which contains strictly exogenous or exogenous variables. Xtabond2, unlike the previous xtabond, instruments the lagged dependent variable using gmm style and iv style and uses SGMM estimator, which provides a much more efficient and consistent estimate than the DGMM estimator.

Do innovation input and innovation output impact firm performance differently?
Panel evidence from Germany

2.1 Introduction

Schumpeter (1939, 1927) was one of the most influential early writers about business cycles, innovation and entrepreneurship. He argued that business cycles are the recurrent fluctuations in the rate at which innovations are introduced into the economy and in the intensity with which entrepreneurs exercise their *sui generis* function of overcoming obstacles to new combinations (Kuznets, 1940). History—according to Schumpeter—contains a few unusual episodes in which groups of exceptionally able entrepreneurs introduce revolutionary innovations which transform existing technologies. During these episodes, economies grow strongly and experience booms where the diffusion of these innovations eventually encourages imitators to swarm into the market and compete away the pioneering entrepreneurs' profits. He further argued that such imitators help to establish the new order as a new equilibrium for the economy. The economy slows down and stagnates, until another set of pioneering entrepreneurs[1] disrupts the equilibrium again with a new set of revolutionary innovations which renders the previous ones obsolete. This precipitates the next boom, and the cycle continues to repeat itself. Such process of entrepreneurial innovation- according to him-is responsible for the regular and commonly observed fluctuations in economic activity which he called the 'normal' business cycle(Parker, 2013).

Indeed, following the seminal work of Schumpeter (1934), innovation has become one of those words that suddenly seem to be on everybody's lips (Fagerberg and Verspagen, 2009). Firms care about their ability to innovate (on which their future competitiveness depends), consultants

are engaged in the business of innovation in persuading companies about the significance of innovation activities, and politicians care about policy designs aimed at stimulating innovation at various levels of government (Christensen and Raynor, 2010). Innovation determines competitiveness and growth and is, more often than not, a life or death ingredient of firms (Utterback, 1994). Truly, a firm has to generate incremental or radical innovation if performance is to be ensured sustainably. And for a firm to undertake radical or incremental innovation, the process has to be supported by entrepreneurship-a crucial ingredient of desired change.

Firms need to generate incremental innovations in order to meet current market demands, but they also need to ensure their long-term survival by preparing radical innovations that reinvent their business and market. If a firm does not innovate or learn, another firm will—and will take over the marketplace. Radical innovation or creative destruction creates discontinuity, affecting the structure of knowledge flow, and may result in dominance of the innovator in the marketplace, eventually leading the innovator to be competent (ibid). In a similar tone, Tidd, Bessant, and Pavitt (2001) argued that large firms face the fate of disappearing if they do not prepare radical innovations for the next generation of products and markets. They observed that almost 40% of firms that made fortune top 500 in the 1980s disappeared due to lack of innovation, and in the 1970s, 60% of firms were acquired as a result of innovation. Furthermore, their analysis showed that the destiny of small firms that do not involve themselves in innovation activities may even be worse as these firms lack the protection that large firms with a large resource base (capital) have. The study, further, indicate that firms that have introduced innovation have undergone creative destruction and, consequently, have improved business, whereas firms that have not introduced innovation have faced enormous problems or have gone out of business.

Clearly, innovation is a crucial tool for firm performance regardless of firm size, age, or type. However, firm performance does not only respond positively to innovation; there are conditions under which a firm can respond negatively to innovation activities, depending on firm-specific effects, skill, labor force training, and factors that directly or indirectly influence innovation. If we take employment as an indicator of firm performance, the introduction of innovation activities at firm or market level would have negative effects on employment growth and, thus, performance of firm. This is because different channels of innova-

tion can destroy existing jobs, resulting in displacement effects, but there are also several mechanisms through which innovation may create new jobs, providing compensation effects (Peters, 2008).

A number of empirical studies prove innovation to be an integral[2] part of firm performance as well as firm competitiveness, making the study of innovation one of the burgeoning fields of research and top policy agendas in industrial policy. These studies range from a classical approach,[3] focusing on two innovation indicators (R&D expenditure and patents) and their impacts on firm growth, to analysis of the effect of product, process, organizational, and marketing innovations on firm growth (Tödtling and Trippl, 2005). The introduction of Community Innovation Survey (CIS)—a standard guideline for the collection and interpretation of innovation data (OECD, 2005)—has even increased studies of firm performance impacts of innovation and, presently, a number of innovation research centers, institutes, and departments have continued to evolve and participate in innovation impact research.

The *Oslo Manual* (OECD, 2005), which classifies innovation into innovation input and innovation output, has identified knowledge generation (Cooke, 2002), knowledge spillovers, and knowledge governance (Audretsch and Feldman, 1996; Bottazzi and Peri, 2003) at firm level as an essential part of spurring and sustaining firm performance. Moreover, some take firm knowledge as an indicator of innovation through share of researchers in a firm and the impact these researchers have on firm performance. Others employ growth theory to estimate the impact of total factor productivity (Lucas, 1988; Romer, 1986), knowledge cluster (Enright, 2003; Porter, 1998, 2008), and knowledge economy (Anselin, Varga, and Acs, 1997; Audretsch and Feldman, 1996; Jaffe, Trajtenberg, and Henderson, 1993; Nonaka and Takeuchi, 1995) on firm competitiveness—all of which directly or indirectly study the role of innovation on firm growth using different methodologies and data.

Recognizing the multiplier role that innovation plays in firm performance (employment, sales, and labor productivity), a number of studies have attempted to analyze the implications of innovation on firm performance. Most of these studies are, however, confined to manufacturing firms where the GDP share (especially in advanced countries) is getting far less than what the service sector is contributing. This essay aims to contribute to this gap by estimating the effects of innovation input and innovation output on the performance of 3,124 German manufac-

turing and service firms using panel data. The study intends to answer three questions: Do innovation input and innovation output affect employment growth of manufacturing and service firms differently? To what extent do innovation input and innovation output affect the sales growth of manufacturing and service firms? Does wage growth respond differently with respect to innovation input and innovation output in manufacturing and service firms? In order to answer these questions, I use eight years (2003–2010) firm-level longitudinal data drawn from MIP, collected by the ZEW, a research think tank. I further analyze the relationships between innovation input/innovation output and firm performance (employment, sales, and labor productivity growth) using the SGMM estimator. In order to achieve the stated objective of the essay and answer the research questions, I measure innovation input by R&D intensity, innovation investment intensity, and total innovation intensity; and proxy innovation output by product innovation to firm, product innovation to market, and cost reduction (process) innovation. The essay—including the foregoing —has seven parts. In the following part, I review literature on the concepts and measurements of innovation; theoretical reflections on innovation-employment, innovation-labor productivity relationships, sales; and the empirical contributions made on innovation-firm performance. The third part presents the added value of the present study and, in doing so, attempts to provide explanations of how the current study contributes to literature. In the fourth part, I introduce the empirical model and estimation strategies. This is followed by description of data and summary statistics. In the sixth part, I present the interpretations of the estimated model results; and finally, in the seventh section, I offer a conclusion.

2.2 Innovation: Concept, measurements, theories and empirics

Innovation attracts scholars, practitioners, policy makers, politicians, and consultants alike. However, the way it is defined and interpreted appears to differ among various actors, depending on various circumstances. In this section, the concept of innovation is presented to provide a general understanding for the subsequent analysis of the paper. The definitions are taken from various sources, most of which are authoritatively built by European scholars, including Schumpeter, the pioneer of innovation.

2.2.1 Concept of innovation

Schumpeter (1934) defined or described innovation in a way that is simple but open to many interpretations: as "the setting up of a new production function." This interpretation covers new commodities as well as those of a new form of organization (such as a merger) and opening up of new markets. Edquist, Hommen, and McKelvey (2001) interpreted Schumpeter's notion of "new commodities" as new technologies or product[4] innovations, adding that within "the setting up of a new production function," new organizational and technological processes evolve which further lead into innovation. In fact, Schumpeter (1934) observed that *innovation* can also refer to a new use or a "new combination"[5] of existing factors, that is, the use of existing technologies or knowledge in a way that they have not been used before. This latter observation is well supported by Nelson and Winter (1993), who argued that most often, invention is successfully commercialized by someone other than the inventor, and it may happen a long time after the invention occurred. Thus, the successful diffusion of a new product or process is required for it to be characterized as innovation.

In a similar tone, Peters (2008) who subscribed Schumpeter's idea of innovation, came up with the view that innovation is "the doing of new things or the doing of things that are already being done in a new way". She elaborated this concept of innovation in five ways: the introduction of a new product or a qualitative change in an existing product (incremental innovation), implementation of a new production or transportation method new to an industry, the opening of a new market, development of new sources for raw materials, and inputs and changes in industrial organization (monopolization of industry). Other experts, including Freeman and Soete (1997), Fagerberg and Verspagen (2009), and Dosi (1988) shared the above views.

Innovation is a required change or novelty[6] where the change is understood by some as *incremental* and by others as *new production* or introduction of outputs. In a similar context, Chen, Zhu, and Xie (2004) defined innovation as an introduction of new [7]or combination of the essential factors of production into the production system where the factors of production include human capital in R&D activities. They defined R&D activities as indicators of innovation and further explained that identifying the sophistication level of innovation production factors, the type of innovation determinants to be used, and the mechanisms un-

der which these factors can be applied in different contexts are integral to understanding the mechanics of innovation.

Indeed, innovation is interpreted in a multitude of ways. It is the competence of organizing and implementing research and development, bringing forth the new technology and product to meet the demands of customers (Plessis, 2007). It involves a new product, new technology, new market, new material, or new combination. Popular words or phrases that are attached to or part of innovation interpretation are "new," "significantly improved," or "original"; and when it comes to strict definition and interpretation, it embraces loose definition. Innovation is also contextualized or expressed by the number of researchers engaged in research business, by the amount of money allocated for R&D, and by the number of patent rights granted or applied per year. It is a process of knowing the extent to which available innovation activities are being implemented as well as providing new mechanisms through which new approaches, inputs, and outputs are provided. Indeed, innovation can be seen as a process that encompasses technical and physical activities that are central in forming product innovations and development routines (Cardinal, Alessandri, and Turner, 2001).

Innovation is also understood as a process of *knowledge accumulation*. This notion argues that a society with a good stock of knowledge is likely to embark on innovation activities better than a society with less HC. It is true that the economically and technologically advanced countries of today are in a better condition in knowledge production and application than the rest of the world where the advancement of these countries is explained by the extent of innovation they are involved in, among other things. Furthermore, Harkema(2003) explained innovation as a knowledge process aimed at creating new knowledge geared toward the development of commercial and viable solutions. It is a process wherein knowledge is acquired, shared, and assimilated with the aim of creating new knowledge, which embodies products and services. It is about adoption of an idea or behavior (incremental innovation) that is new to the organization.

Innovation as a process can also be conceptualized in terms of discovery and implementations of changed components. It is a mechanism of intervention that aims at destabilizing an existing system with a view to upgrade or completely transform the existing system into a new form (Gloet and Terziovski, 2004). The authors distinguish *radical* and *incremen-*

tal innovation from one another. Incremental innovations involve extension or modification of existing products and are usually classified as market-pull innovations. Incremental innovation does not require significant departure from existing business practices and is likely to enhance existing internal competencies by providing the opportunity to build on existing know-how. Radical innovations, on the other hand, are likely to be competence-destroying, often making existing skills and knowledge redundant necessitating different management practices. Radical innovations may put a business at risk because they are more difficult to commercialize. They are considered crucial to long-term success as they involve development and application of new technology, some of which may change existing market structures. Firms that facilitate radical and incremental innovation are more successful than firms that focus on only one or the other.

Still an authoritative (and the most standard) interpretation of innovation is from *Oslo Manual* (OECD, 2005). The manual defines innovation as the implementation of a new or significantly improved product (good or service) or process or a new marketing or a new organizational method in business practice, workplace organization or external relations. The minimum requirement for an innovation is that the product, process, marketing method, or organizational method must be new or significantly new to a firm or market. Indeed, the manual identifies four types of innovation: product, process, marketing, and organizational innovation.

The first two—product and process innovations—are the most popular and are closely related to the concept of technological product innovation and technological process innovation. A product innovation is defined as the introduction of a good or service that is new or significantly improved with respect to its characteristics or intended use. This includes significant improvements in technological specifications, components and materials, incorporated software, user friendliness, or other functional characteristics. In the service sector, product innovations include significant improvements in how services are being provided (for instance, in terms of their efficiency or speed), the introduction of new functions or characteristics to existing services, or the production of entirely new services. For example, design is an integral part of the development and implementation of product innovation. Nevertheless, design changes that do not involve

noteworthy alteration in product's functional characteristics or intended uses are not product innovations.

The other two innovations—which are not popularly recognized due to measurement problems—are marketing and organizational innovations. A marketing innovation is the implementation of a new marketing method that includes substantial alterations in product design, packaging, product placement, product promotion or pricing. The purpose of the introduction of marketing innovation is to address customer needs, opening up new markets, or newly positioning a firm's product on the market, with the objective of increasing firm's sales. However, seasonal, regular, and other routine changes in marketing instruments are not considered to be marketing innovations. For changes to be marketing innovations, they must involve marketing methods not previously used by a firm. In fact, the fundamental feature of marketing innovation compared to other changes in a firm's marketing instruments is the application of marketing method not previously used by the firm (OECD, 2005). On the other hand, organizational innovation is the implementation of new organizational method in firm's business, workplace organization, or external relations; as such, these innovations are intended to increase firm's performance by reducing administrative costs or transaction costs, improving workplace satisfaction, gaining access to non-tradable assets, or reducing cost of supplies. However, changes in business practices and workplace organization that are based on organizational methods already in use are not assumed to be organizational innovations.

To sum up, an important aspect of innovation characteristics is that all kinds of innovations (product, process, marketing, and organization) are interdependent. For example, it is hardly possible to create product innovation without having had process or cost reduction innovation; at the same time, the introduction of cost reduction innovation can, indeed, be influenced by the extent and nature of product innovation. Realization of product and process innovation without the restructuring of organizational form or introduction of new organizational systems would be really difficult, if not impossible. Innovation can be interpreted at different stages: input, intermediary, and output. With this in mind, I now turn to brief discussions on indicators and measurement of innovation.

2.2.2   Innovation indicators and measurement[8]

Because the nature and character of innovation is comprehensive (left to various interpretations), identifying full-fledged innovation indicators appears to be complex and demanding. However, there is a convergence of the views that innovation can, indeed, be expressed by a set of standard tools (Gault, 2013). So far, the most authoritative standard indicators of innovation (innovation input, intermediate innovation, and innovation output) are provided by the *Oslo Manual* (OECD, 2005) and the European Innovation Scoreboard (EIS). The indicators provided by these sources proxy innovation activities at firm level in advanced countries—most particularly for OECD countries. These indicators include expenditure on R&D (intramural R&D and extramural R&D), number of patents applied or granted per 100,000 population, innovation investment expenditure (expenditure to acquire machinery and equipment in order to implement new or significantly improved products or processes), extent of knowledge used (share of employees with university degree or share of employees in high-tech and KIS), scope of internal or external training aimed at developing or introducing innovations, level of internal or external marketing activities performed to introduce new commodities (market research, market tests and launch advertising), and level of product design and other preparations to realize actual implementation of product and process innovations, among others.

Most importantly, the intensity of R&D, innovation investment intensity, extent of high-tech applied, share of highly skilled employees or researchers in high-tech firms, patents, and intellectual properties are used as common indicators of innovation. The variable R&D intensity is measured by aggregates of public, business (private sector), and university expenditures as percentage of GDP whereas the share of university-level graduate employees is traced by percentage of total labor force employed in high-tech and medium-high-tech, knowledge intensive services and manufacturing sectors (including science and engineering graduates). Innovation is also measured by the share of university-level graduate employees, regardless of the kind of job. Tertiary education as a gauge of innovation has, however, become questionable due to the fact that most graduates, particularly in advanced countries, end up working in non-scientific or non-knowledge intensive service activities.

A note should be made about the high-tech indicator of innovation in the manufacturing and services sectors. In the former, high-tech as a

gauge of innovation is measured by the share of sales of a firm due to innovation to total sales of a firm due to innovation and non-innovation. On the other hand, in the service sector, high-tech is measured on the extent of knowledge-intensive services (KIS) such as high-tech KIS, market KIS, and less-KIS[9] (Greenhalgh and Rogers, 2010).

The various indicators of innovation can be grouped under two major categories: intangible and tangible indicators, where the former focuses on knowledge capital, which includes HC, intellectual capital, and organizational capital and, accordingly, employs one or a combination to express innovation (Meyer, 2005). The measurement of innovation through HC takes the stock of knowledge and skills of individuals able to generate innovation, and intellectual capital represents technical inputs that engender innovation process. Organizational capital refers to business models and process networks and alliances and special competencies of a firm such as marketing or design, which eventually leads to innovation. An intangible indicator of innovation *per se* doesn't directly measure innovation; it instead measures investments that lead to innovation and make specific assumptions about activities that lead to innovation (science is important, but accounting is not).

Tangible indicator of innovation emphasis on expenditure made to innovation indicators including investments for building HC, human resource training, R&D, and patents and trade secrets. The HC component—unlike the intangible indicator—as proxy of innovation takes expenditure to educate or scale up knowledge of employees, to provide training for employees as well as for hiring individuals who already have the training and skills required for the job or strategically access knowledge and skills not internally available. Some companies use a combination of hiring trained staff and training internal staff. Anecdotal evidence shows that innovation is not only a function of engineering or marketing activities but also a mix of highly trained workforce of non-engineering disciplines (Aizcorbr, Moylan, and Robbins, 2009; Stone, Rose, Lal, and Shipp, 2008).

The tangible indicators of innovation are also increasingly contextualized in terms of the utilization level of information communication technology infrastructure. The amount of money allocated for the use of ICT as a share of GDP has, for example, increasingly become an important proxy for measuring innovation. Areas such as the purchase of servers, lying of fiber optic cables, and software have been added to national ac-

counts. The measurement of innovation through tangible and intangible indicators of innovation can best be presented in the innovation production function (IPF), which is indicated in Figure 2.1 (Guan and Chen, 2010). Focusing on technological innovation, the procedure begins with the use of technological innovation inputs (upstream) where sub-processed technological R&D is conducted from original R&D technological innovation inputs to generate incremental technological innovation outputs (intermediate outputs in terms of the whole innovation process). The sub-process operation is related to such activities as researching, developing, testing, and learning by doing or importing.

Figure 2.1
A framework for measuring innovation
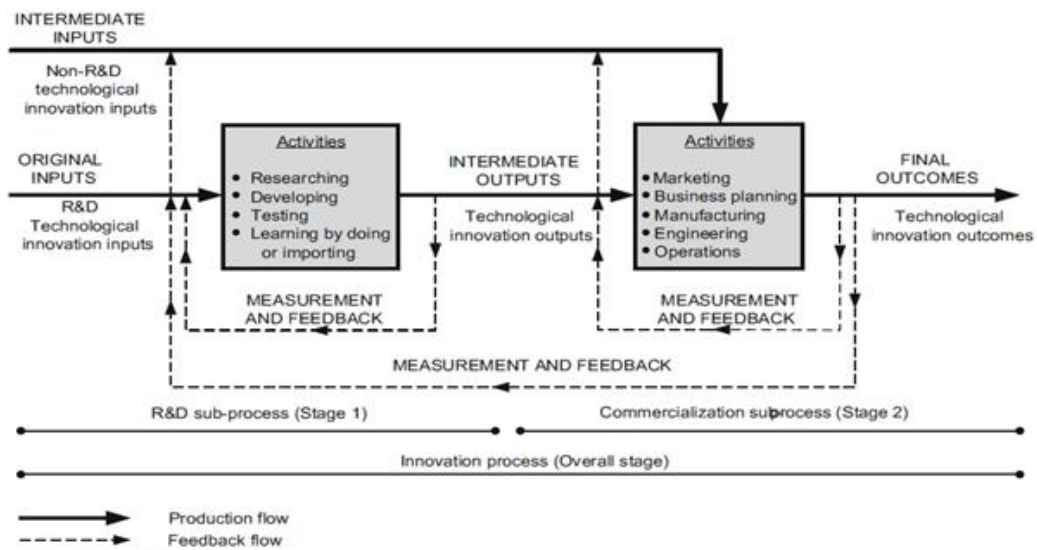
Source: Guan and Chen (2010)

The sub-process is linked with the second stage, the downstream technological commercialization, from incremental technological innovation outputs to technological innovation outcomes. The second sub-process stage operation supports such economic activities as marketing, business planning, and manufacturing. The two sub-processes are rela-

tional and not necessarily independent, for they are connected by technological innovation outputs, implying that intermediate technological innovation outputs have double identities: output in the first sub-process and input in the second sub-process.

The application of innovation process production is subject to external non-R&D technological innovation inputs. These non-R&D technological innovation inputs participate in the downstream technological commercialization process with internal/in-house R&D technological innovation outputs from the upstream indigenous R&D sub-process. The innovation measurement framework further indicates that it is the intertwined efforts of R&D and non-R&D technological innovation inputs that, in due course, result in technological innovation in the marketplace from the production perspective. These authors have included non-R&D technological innovation inputs as innovation indicators in order to overcome the difficulty of separating the contributions of R&D and non-R&D technological innovation inputs to technological innovation outcomes. This reveals that technological innovation process is, at least, a network of a two-stage production framework. The integrated measurement framework not only leads to assign primary importance to the upstream indigenous technological R&D performance but also indicates the necessity of attaching particular relevance to downstream technological commercialization performance in the economic sense. They argue that the net framework is able to provide an effective approach to investigate overall component and performances of the innovation process production.

2.2.3 Innovation and firm performance: Theoretical reflections

In the previous sections, I discussed the conceptual underpinnings, indicators, and measurement of innovation. In this section I review theoretical literature related to the implications of innovation on firm performance through employment, sales, and productivity. However, because theoretical literature on the relationship between innovation and sales growth is not very much known, I focus on theoretical dynamics of innovation and employment as well as on innovation and productivity.

On the relationships between innovation and employment

Many people assume that the relationship between innovation and employment at firm level is straightforward and positive. Nevertheless, as

long as the association can be factored by the feature of existing production technology and the nature of technological innovation (product or process innovation), type of labor (labor-intensive or capital-saving, neutral, skill-biased), magnitude of innovation (radical or incremental innovation), and manifestation (disembodied or factor-embodied), there is no certainty that innovation will have a positive impact on employment. The uncertainty can also be attributed to consumer preferences, competition on commodity and labor markets, and the qualification structure of the labor force (Peters, 2008, 2009).

For example, looking into the implications of product innovation on employment, one would find inconclusive impacts. It is possible that product innovation can lead to new products on the market, which stimulates new demand. This increasing demand allows innovating firms to hire more workers. Accordingly, from the direct effect of product innovations on employment, we would expect a positive relationship (Lachenmaier and Rottmann, 2011). On the other hand, there is also a less obvious, indirect effect in situations when a firm introduces a new product to the market, when there are no direct competitors, and thus the innovating firm profits from a temporary monopoly position until other firms introduce similar or better products. In this scenario, the firm can exploit its monopoly power and maximize its profits. This can lead to a decrease in output and, therefore, to a reduction in employment. In particular, if the new products are substitutes for existing products of the firm, the effect is not clear. New workers can be replaced by old workers—a decrease in labor demand is possible if production of new products requires fewer workers than the production of the old products. This could happen if, for example, labor intensive technology were to be introduced. This effect is opposite the direct effect, indicating that the overall effect of product innovations on employment is unclear in principle (García-Manjón and Romero-Merino, 2012).

If the innovating firm produces more than one good, the effect on employment depends on synergies in production as well; the higher the synergy, *ceteris paribus*, the lower the impact on labor demand (Peters, 2008). Furthermore, there are indirect employment effects that depend on substitutability between old and new products. If a new product is able to replace an old one partially or fully, labor demand for the old product will decrease, and the overall effect can, indeed, be unclear for the innovating firm. However, in the case of complementary demand

relationships, innovation causes the demand for previously existing products as well as employment to increase (Harrison, Jaumandreu, Mairesse, and Peters, 2008). Moreover, the inconclusive theoretical explanations of the impact of product innovations on employment can also depend on the extent of product novelty. Vernon (1966) argued that each product novelty follows a life cycle; according to this interpretation, market novelties can initiate the cycle of the product or even the sector. Younger sectors are less mature—as consumers are not yet well-equipped—and, therefore, experience higher demand increases (Greenan and Guellec, 2000). Eventually, market novelties would tend to result in higher output and employment growth. On the contrary, firms develop innovations to alter market structures and to reduce competitive pressure. If an innovation development strategy is successful, and if own price elasticity for the new commodity is lower compared to the old product, then product innovations result in higher prices, decreased output, and decreased employment (Smolny, 1998). This tends to be dominant in cases where market novelties define temporary monopoly. Furthermore, because market novelties are commonly associated with uncertainty and risk of failure, such phenomena can eventually result in a lowering effect on employment growth.

Process innovation, like product innovation, can have inconclusive effects on employment (Blechinger, Kleinknecht, Licht, and Pfeiffer, 1998; Katsoulacos, 1986; Stoneman, 1983). The direct effect of process or cost reduction innovations could be obvious in situations where the process innovation helps a firm to produce the same level of output with fewer workers, indicating a negative effect of process innovations on employment. Process innovation can also have indirect effects on employment when a firm raises its productivity; it will reduce its production costs and will tend to increase production. The increase in output level allows a firm to hire additional workers. This effect might outweigh the direct effect; therefore, it may not be possible to draw a definite conclusion about the direction of the effect of process innovations on employment (Lachenmaier and Rottmann, 2011). For example, if the productivity of a firm is increased due to process innovation, it implies that the firm can produce the same amount of output with less input and lower costs. However, we do not have information on whether the process innovation introduced invites many individuals to participate in the process and improve productivity or has actually allowed only a few people to be-

come involved in the process. Under such circumstance, the immediate extent of the employment effect in the innovating firm depends on current production technology (and, thus, the substitutability between input factors) and on the direction of technological change (Peters, 2008).

The implication is that this phenomenon will have a negative effect on employment in the short run, resulting in the displacement effect of process innovations. The primary purpose of process innovation is the introduction of methods to reduce costs associated with production of goods or services. Despite the displacement effect of process innovations, it is possible an innovative firm can pass cost reduction on to output prices, which will result in a higher demand for (and output of) the product. The compensating price effect depends on the amount of price reduction (i.e., whether it is proportional), the demand price elasticity, the degree of competition, and the behavior and relative strength of different agents within the firm.

The more intense the competition on the commodity market and service market, the higher the probability that cost reductions can be transferred to output prices. On the other hand, a firm's owners may be interested in using market power to increase their profits to offset how unions may seek to transform any gains from innovations into higher wages, which can minimize compensation effects (Nickell, 1999). Under such conditions, compensating mechanisms increase labor demand, so employment change in the innovating firm is not clear. Overall, we learn that it is indeed difficult, if not impossible, to have a clear judgment on whether innovation, regardless of type, could have a positive or negative impact on employment growth. This inconclusive nature is depicted in Table 2.1.

Table 2.1
Theoretical explanations for firm-level employment effects of innovation

Innovation category	Effect	Transmission mechanisms	Direc- tion[a]	Determinants[b]
Process innovation	Productivity effect	Less labor for a given output	-	Substitutability between input factors, direction of technical change
	Price effect	Cost reductions can be passed on to output prices, enhance output	+	Amount of price reduction, price elasticity of demand, competition, agents' behavior
Product innovation	Demand effect	Demand increase by new product	+	Competition, reaction of competitors, synergies in production
	Indirect effect	Demand effects on old products	+/-	Demand relationship between old and new products
		Productivity difference between old and new products	+/-	Production technologies

Source: Peters (2008). Note: (a) + indicates a positive employment effect, - is a negative employment impact, and +/- represents that the employment effect could either be positive or negative; (b) shows that lists of employment determinants are not necessarily complete.

On the relationships between innovation and labor productivity

The nexus between innovation and labor productivity can also be inconclusive, depending on the type of innovation introduced, duration, and intensity. It is very possible that the elasticity of labor productivity with respect to innovation could even be negative. The fact is that although innovation spurs productivity in the long run, there is a range of theoretical arguments and underpinnings that suggest that, in the short run, innovation can lead to productivity loss. There are three main strands of justification for a possible negative relationship between innovation and productivity.

The first justification has to do with the difficulty that very productive firms with less expertise that switch to new technologies will be less productive than if they stay with their existing technology (Jovanovic and Nyarko, 1996) This argument centers on the *learning lag principle* that

working with a new technology typically entails some costs that result in negative consequences. In the presence of a new technology, the more productive firms face the prospect of losing the knowledge that had accumulated with existing technology. The more radical the new technology, the more the firm has to lose what it has accumulated so far—but the more it will potentially gain in future productivity growth. Oddly, in the presence of a huge technological leap, the more productive firms tend to be the most reluctant to introduce new technologies: the learning disincentive of jumping to new technologies is proportional to the firm's proficiency in its existing technologies.

The *principle of the learning lag* explanation predicts that innovating firms will exhibit a short-run productivity drop due to the need to acquire the expertise to work with new technology. It further predicts that the more productive the firm and the more radical the new technology, the more difficult it is for the firm to jump into the new technology. Consequently, very productive firms faced with significantly new technological opportunities may be unable to innovate; and eventually, innovating firms will exhibit not only productivity declines but also productivity that is inversely related to innovation.

The second theoretical justification for the negative impact of innovation on productivity in the short run has to do with *technology and organizational rigidities*. This theory argues that when innovation emerges, firms do not perform as well as existing leading firms may be hesitant to adopt new technologies that may bring about significant productivity loss (Christensen and Bower, 1996; Leonard-Barton, 1992; Utterback, 1994; Young, 1991; 1993). This theory is based on the idea that firms face a cognitive or behavioral limitation that prevents them from entering new technologies, not only because these firms exhibit poorer performance than existing firms but also because the actual economic results of the firm are affected in the short term when experimenting with new technologies. To better understand whether innovation could have negative implications for the productivity of labor, it is necessary to take economic and organizational effects as well as part of that analysis, because organizational rigidities could have multiplier implications for productivity growth based on the success or failure of innovation (Henderson, 1993). Nevertheless, considering both dimensions is rarely done, and the few firms that do consider both dimensions revert again to the long-term effect (Bierly and Chakrabarti, 1996; Tripsas, 1997).

Technology and organizational rigidity—unlike the learning lag explanations- theory, considering that averseness to innovate does not depend on the level of productivity alone—may be contingent on the organizational rigidity of the firm. Measuring rigidity is difficult, but if the argument runs that the most successful, productive firms are those that stick closely to existing routines, then the same prediction in terms of levels of productivity can be assumed to emerge from these theories. So, again, this theory predicts a negative relationship between innovation and productivity growth.

The third strand of literature considers that innovation is often accompanied by costs associated with scrapping replaced inputs and adjusting to the new characteristics of inputs and that these *adjustment costs* may lead to productivity loss (Bessen, 2002). Basic explanations for these adjustment costs include imperfect expectations or short-run supply inelasticity in factor markets, as reviewed by Hubbard (1998), when capital is the factor considered. However, even assuming that a firm does not face information problems or imperfections in factor markets, it is still likely to face adjustment costs. Among other things, adjustment costs may include severance payments (to outgoing workers), search costs associated with recruitment of new employees (advertising and screening), and training costs (including on-the-job training, entailing loss of time devoted to production by veteran workers as they train the new ones). All these activities tend to have negative feedback on labor productivity in the short run (Hamermesh and Pfann, 1996).

Adjustment costs reduce productivity or efficiency during the period of transition from reassigning workers to new machines (including the learning-by-doing it takes to fully utilize the new equipment), shifting resources from production to installation of new machinery, and the costs of scrapping old equipment (Lerner, 1953; Lucas, 1967; 1967; Treadway, 1971). Because there is a lack of secondary market for scrapped capital goods, new investment is mostly irreversible; therefore, uncertainty about future shocks makes firms hesitant about investing capital (Abel and Blanchard, 1983; Dixit and Pindyck, 1994).

Overall, although the three theories show the negative labor productivity effects of innovation in the short run, these justifications do not tell us the kinds of innovation that could bring about discouraging effects on labor productivity. These theories also do not provide justification for which kinds of innovations (such as innovation inputs and innovation

outputs) have a negative impact on productivity in the short run, in the long run, and in what manner. Existing empirical studies do not provide sufficient knowledge on the implications of different forms of innovation on labor productivity performance, either in the short run or long run, partly due to a lack of adequate innovation panel data and partly due to a lack of innovation measurement problems.

2.2.4 Innovation and firm performance: Empirical contributions

In the above sections, I discussed the theoretical underpinnings of the implications of innovation on firm performance (i.e., on employment and labor productivity). The review in the above section showed that innovation does not always have a positive impact on firm performance: innovation can indeed have a negative consequence on the performance of firms, depending on the nature and kind of innovation, time and duration of innovation, and the outside environment (such as number of competitors and consumers among others). In this section, I provide some empirical contributions made on the implications of innovation on firm performance[10] in order to provide insights into what sort of research has so far been conducted and, in doing so, how the present research would further contribute. The review first looks at the relationships between innovation and employment, then innovation and sales performance, and finally influence of innovation on labor productivity.

Innovation and employment

Entorf and Pohlmeier (1987) and Zimmermann (1991) employing cross-sectional data offered useful insights on the relationship between innovation and employment. While the former study analyzed the employment impact of innovation using micro data in Germany and found a positive effect for product innovations and no significant impact for process innovation, the latter study for the same country concluded that technological progress was responsible for the employment decrease in 1980. However, Zimmerman focused on the labor-saving technological progress—an approach at odds with the content and context of the studies of Entorf and Pohlmeier, whose approach was not on labor-saving technology. A similar attempt by Blanchflower and Burgess (1998) found a positive relationship between process innovation and employment. They estimated the employment effects of innovation using data from innovation surveys of the UK and Australia. In the three studies, process inno-

vation appears to have had different implications on employment: in Germany it was not robust, whereas for the UK and Australia, it had a positive effect, confirming the unpredictable implications of process innovation. Castillo, Maffioli, Rojo, and Stucchi (2014) using a combination of fixed effects and matching for small and medium enterprises in Argentina found that both process and product innovation support increased employment and wages, with a higher impact on employment. In addition, they identified that product innovation support had a larger effect on wages than process innovation support.

Most innovation studies at *firm level* use short panel data. For example, Brouwer, Kleinknecht, and Reijnen (1993) use two Community Innovation Surveys (CIS) for the Netherlands to estimate the effects of innovation on employment growth. Taking R&D expenditure and product-related R&D expenditure as indicators of innovation, their study reveals that employment is negatively impacted by R&D expenditure, whereas product-related R&D has shown a positive impact on labor demand. At least two things can be observed: because only two waves are used, it is hardly possible to be sure whether the positive or negative impact would continue for an extended period of time. Besides, as the panel spans only two years, it is not possible to use lagged values to counter the problems of firm-specific effects as well as endogeneity problems. Similarly, Greenan and Guellec (2000), who used the French Innovation Survey for the period 1986–1990, found that both process innovation and product innovation have positive effects on employment, with the latter being higher. Nevertheless, I could not find evidence on whether the model they used fulfils model specification tests, including absence of serial correlations and over-identification problems. Jaumandreu (2003) who closely followed the approaches of CIS from the Spanish CIS3 for the year 2001, found that process innovation does not have a responsible net employment displacement, although product innovations lead to positive employment. Peters (2008) used a similar approach for Germany and found that in the manufacturing sector, product innovations brought positive effects on employment, whereas there is no significant difference in the size of the effect between products new to the market or products imitated by the innovating firm. For process (rationalization) innovations, she found a negative effect.

At cross-country level, based on CIS3 data, analysis of the labor demand implications of innovation effects in France, Germany, Spain, and

the UK also provides useful insights (Harrison et al., 2008). The authors show that product innovation has positive effect on employment growth and further demonstrate that displacement and compensation effects of process innovations are present in the manufacturing sector. Lachenmaier and Rottmann (2011) did a panel analysis over 20 years and, using a dynamic model, and found that the first and second lag of employment, lagged product innovation, and lagged process innovation have a positive and robust impact on employment growth in almost all of the considered variables. Moreover, unlike the estimations of Jaumandreu (2003), Peters (2008), and Harrison et al. (2008), the contributions of Lachenmaier and Rottmann (2011) show that process innovation compared to product innovation tends to have higher effect on employment, and most of the effects have been significant for the first lags and second lags. The exception is for product innovations with patent applications, which also have contemporaneous effects on employment. For innovation inputs, Lachenmaier and Rottmann (2011) only found significant effects for the second lag, giving further support to innovation variables, as is evidenced by a longer lag for the effect of innovation input on employment than for innovation output. Unfortunately, as their study is limited to manufacturing firms, it is not possible to say with certainty how the implications of the estimation could behave if service firms were included.

Other studies that use a *dynamic panel* include those of van Reenen (1997), Rottman and Ruschinski (1998), and Piva and Vivarelli (2005). In the UK, van Reenen (1997) was able to obtain positive causal effects of product innovations on employment by matching innovation indicator variables with major innovations counted by Science and Technology Policy Research Unit (SPRU) and by controlling for fixed effects and endogeneity is. It should, however, be noted that unlike other European countries' firm-level innovation studies, van Reenen's selection of firms was restricted to firms listed in the London Stock Exchange category, which in many circumstances deviates from the common innovation indicators used in European countries as well as his measure of innovation differs from the method used by most European countries, as SPRU innovation counts refer only to the major and most influencing innovations and do not measure minor innovative progress. Rottman and Ruschinski (1998), who used the Ifo[11] Business Survey of the years 1980–1992 for Germany, found that product innovation affects employment

positively, but no significant effect is traced for process innovations. In Italy, Piva and Vivarelli's (2005) estimation of employment impacts of innovative investment revealed positive and robust impact; and Cainelli, Evangelista, and Savona (2006), who used Italian CIS2 and System of Enterprise Accounts (SCI) in the service sector, showed that innovation has positive and robust impact on employment growth. Moreover, growth of labor demand in the service sector has encouraged service firms to innovate.

Indeed, employment growth at firm or industry level can be affected by a number of factors other than innovation. For example, Cingano and Schivardi (2004) who measured productivity growth through employment growth found that productive concentration is associated with slower employment growth at the city-sector level. In particular, they found that doubling the share of sectoral employment in a given location reduces average employment growth in same sector by 0.75% per year. The study also showed that partial elasticity of employment growth to city-size is estimated to be negative and substantial. Doubling employment in a given city- ceteris paribus-tends to reduce the growth rate by more than 1% point per year over the subsequent period. Moreover, they identified that variety-size and competition indicators- which apparently have no direct effect on total factor productivity growth do significantly affect local employment, that there is positive partial elasticity of employment growth with respect to average firm size and negative employment growth with respect to productive diversity in the city.

Summing up, the reviewed studies seem to focus on product and process innovations and estimate the extent to which these innovations affect employment growth. In addition, they use CIS methods (OECD, 2005), as rightly pointed out by Fagerberg and Verspagen (2009); Fagerberg and Sapprasert (2010); Schmidt and Rammer (2007); and Damanpour, Walker, and Avellaneda (2009). Furthermore, literature shows that manufacturing sectors have been extensively reviewed, whereas service sectors, which take the largest value added share in today's economy, have not been covered well. In terms of data type, short panel data has been used in most of the reviewed literature; it tends to lack consistent and efficient estimations that eventually would affect the replication and policy implications of the contributions, if any. The present study intends to address these.

Innovation and sales performance

The model developed by Crepon, Duguet, and Mairesse (1998) play great role in analyzing the dynamics between innovation and sales of a firm. The model has three stages: the decision to innovate (determinants of innovation), the impact of R&D on innovation, and the impact on productivity growth. Using the second stage and R&D intensity[12] as an indicator of innovation, they found that a 10% increase in R&D intensity has induced a 5% increase in sales in manufacturing firms in France, but no attempt is made on service sectors that take the largest share of the economy.

Furthermore, using R&D as an innovation indicator, Del Monte and Papagni's (2003) analysis in a panel of Italian firms confirmed that the effect of R&D on firm growth (sales) is greater in the traditional sectors than in sectors with high research intensity. This result appears to be contrary to the established fact where firms that have a high orientation to research are likely to have positive and strong effect on firm growth than firms that use less research intensity. This result can be attributed to the peculiarity of Italian traditional and small business–based economic systems that enjoy competitiveness with respect to foreign firms. Some studies, which find a negative or no significant implication of innovation on firm growth or sales growth, tend to reject the view that innovation increases sales. The insights of Geroski, Machin, and Walters (1997); Bottazzi, Dosi, Lippi, Pammolli, and Riccaboni, (2001); and Geroski and Mazzucato (2002) provide evidence. Dosi, Marsili, Orsenigo, and Salvatore (1995) showed that investigations made at different levels and times of analysis yield significantly different estimates of the relationship between innovation and sales growth. These scholars argued that the idiosyncratic bundles of products and the level of observation at which empirical analysis is conducted is not uniform to track the processes of learning, innovation, and competition. Consequently, the results of the implications of innovation on sales growth at firm level can be positive, neutral, or negative. Such observations are also supported by Tether (1998), who suggested that a finer-grained level of analysis is required to account for technological and economic differences and alternative orientations in product strategy across organizations (Siggelkow, 2003). In their view, ignoring heterogeneity can bias the computed rate of innovativeness and of its implications to the point that fairly inaccurate inferences can be drawn from inter-firm comparisons.

An interesting study in service firms comes from Cainelli, Evangelista, and Savona (2004), who used Italian CIS2 data to estimate the impacts of innovation on sales growth on the basis of innovation introduced between 1993 and 1995 and sales growth observed in the three following years (1996–1998). They found that innovating firms consistently outperform non-innovator in terms of growth, that a strong positive relationship exists between innovation and subsequent growth, and that growth is strongly linked to previous investment in innovation activity. In a subsequent analysis of the same data set, Cainelli et al. (2006) examined the interaction between innovation and firm performance in more detail and concluded that there is a two-way relationship: innovative firms outperform non-innovator, but better-performing firms are also more likely to innovate and to devote more of their resources to innovation. They concluded that there is "a cumulative self-reinforcing mechanism" linking innovation and performance. The drawback of the insight is that because the panel data cover only three years, it is not possible to use SGMM, which takes into account levels and differences and would have provided better and more consistent estimation. The study of Choi and Williams(2014) in Chinese firms showed that innovation intensity and knowledge spillovers positively impact sales growth. Moreover, they found that a U-shaped relationship for depth of innovation and an inverted U-shaped relationship for diversity of innovation.

Few scholars use advanced models to analyze the dynamics between innovation and sales growth. An important piece of work in this regard is by Yang and Huang (2005). Using a GMM model for seven years (1992–1998) data they find that R&D intensity has a positive and statistically significant impact on electronics sales. The study also shows that R&D policies that stimulate firms to devote more R&D effort enable them to have superior sales. However, because the study is restricted to electronics firms, it is not possible to know whether the observed sales performance impacts of R&D also apply to other manufacturing or service industries.

Some intellectuals use innovation outputs instead of innovation inputs to investigate the relationships between innovations and firm profit—one of the indicators of firm performance. For example, Geroski, Machin, and Reenen (1993), after controlling for non-innovation[13] variables and using lagged values,[14] find two major results. First, product innovation to firm has a positive effect on profitability with the level of the

effect being rather modest in size. It is, of course, possible that this kind of reward is commensurate with the efforts made by firms themselves, which could be accounted for by control variables. The second main result shows that although innovating firms seem to enjoy higher profit margins because of the specific innovations they introduce, substantial permanent differences in the profitability of innovating and non-innovating firms also exist that are not closely timed with introduction of specific innovations. These differences, other than innovation intervention, may reflect generic differences in competitive ability between innovators and non-innovators, and they seem to be associated in a very general way with the process of innovating. The differences also enable innovative firms to realize the benefits of spillovers more fully than non-innovative firms. Furthermore, the result shows that innovative firms enjoy higher margins because they have larger market shares than non-innovators, and margins associated with possessing a market share of a given size are higher for innovating firms. These conditions may reflect the indirect effects of specific innovations introduced by these firms, or they may signal a more fully developed set of internal capabilities. Overall, they provide good insight but fail to classify product innovation into product innovation to firm and product innovation to market, apart from not including innovation inputs.

Contradicting Geroski, Machin, and Reenen (1993), Del Monte and Papagni (2003) estimate that the impacts of R&D on profit does not get any meaningful significant impacts. The failure of R&D and more general innovation in not delivering large profits could be attributed to the case that innovative firms might have been followed by many imitators. Or it could be because an increase in market share of the innovative firm does not translate into higher profitability. Furthermore, an important note to observe is that while Geroski, Machin, and Reenen (1993) use an innovation input (R&D) indicator, Del Monte and Papagni (2003) use product innovation. These different indicators could have different implications on firm impacts, as observed. Jefferson, Huamao, Xiaojing, and Xiaoyun (2006) analyzed Chinese manufacturing firms between 1995 and 1999 and found that sales growth is associated with increased innovation activities, especially in larger state-owned firms and local government collectives. García-Manjón and Romero-Merino's (2012) analysis of R&D and firm (sales) growth among 754 top European R&D spending

firms over the period 2003–2007 provides a positive effect of R&D intensity on sales growth. The results, using OLS, quantile regressions, and SGMM estimators show that the strong association is more intense in high-growth firms and is especially significant in high-technology sectors. The performance, and particularly the survival, of firms depend on factors other than innovation. For example, Fritsch, Brixy and Falck (2006) have shown that regional characteristics play a rather important role for firm survival (performance) and that introducing regional dimension leads to considerable improvements of estimation results. They further identified that regional dimension is also reflected in a remarkably high level of neighborhood effects. However, if regional characteristics were purged by applying GMM, then either other factors could impact firm survival, or no effect could have been realized.

Some scholars employ cross-sectional data to investigate the dynamics between innovation and sales growth. Baldwin and Lin (2002), for example, used year 1993 Canadian Survey of Innovation data in manufacturing firms to show that the presence of R&D activities increases production of product and process innovation by about 24% and 15%, respectively. This should, however, be interpreted with caution because the data's cross-sectional nature cannot capture firm-specific unobservable effects that could result in the correlation of innovation and error terms, which would eventually result in problem of endogeneity. Indeed, cross-sectional studies are least preferred for innovation studies because innovation, by virtue of nature, takes some time to be realized.

Innovation and labor productivity

Most innovation-productivity relationship empirical studies are based on the contributions of Griliches(1995) and Crepon et al. (1998). Innovation scholars including Hall and Mairesse (2006), Mairesse and Mohnen (2005) have, for example, extensively used this approach to provide great contributions on the implications of innovation on firm productivity. Other scholars such as Segarra-Blasco (2010) have used a production function of knowledge by relating R&D, number of patents, and share of innovative sales to innovation in order to analyze the nexus between innovation and firm productivity. The knowledge production function as proxy of R&D and of productivity is identified by new growth theory (Romer, 1986).

Of course, the productivity of a firm depends on the market volume of the firm which in turn is a function of innovation related activities. It is common that firms that have higher market shares are likely to involve in innovation activities and invest in R&D in better conditions than firms that have less market shares. For example, the study of Miguel-Benavente (2006), who employed Crepon et al. (1998), showed that larger firms and firms with higher market shares and higher percentage of innovative sales are found to have higher R&D intensity implying a positive R&D activity and sales growth. However, contrary to many research findings, he found that expenditure on R&D does not contribute to productivity for Chilean firms (even controlling size, industry, and demand pull), reflecting the different circumstances in developing Latin American economy compared to advanced countries where the CDM model works. His insight does not match with that of Crepon et al. (1998), who found for France that an increase in sales due to product innovations of 10% corresponds to a 13% increase in the labor productivity of firm. The application of the same approach or model does not guarantee one to have similar results because productivity can differ by firm age, size, and type.

An interesting contribution with respect to determinants of firm productivity comes from Segarra-Blasco (2010), who undertook an empirical analysis of the impacts of innovation on labor productivity in Spanish manufacturing and service sectors. Using three years' innovation data, he found that labor productivity is directly affected by R&D intensity. He further found that R&D intensity presents positive marginal elasticity on labor productivity in all estimations: 7.9% in high-tech manufacturing industries, 6.0% in low-tech manufacturing industries, 11.7% in high-tech KIS, and only 2.5% in other KIS. Despite these numbers, although firm size has a positive effect on productivity in manufacturing industries, it is not in services; and firms that engage in export are observed to have increased their productivity, especially in low-tech manufacturing and service industries. This is one of the few studies that attempt to analyze the productivity effects of innovation in both sectors. Although his contribution to the existing knowledge was of great significance, it failed to employ adequate innovation indicators because he took only innovation input variables as indicators of innovation.

There are also other studies that estimate the impacts of innovation on productivity in manufacturing and service sectors. These include the

works of Lööf and Heshmati (2002) in Sweden, who provided evidence on the responsiveness of the growth of value added per employee, sales, and profit with respect to innovation in manufacturing and service firms. They measure innovation by R&D expenditure, non-R&D expenditure activities, purchase of machinery and equipment, industrial design expense related to producing new products, expenditure on education directly related to innovation activities, and some marketing expense. The estimation discloses that the likelihood of innovating rises with firm size and capital intensity in both manufacturing and services. Nevertheless, Lööf and Heshmati (2002) found that after controlling for industry and obstacles to innovation, innovation intensity is not constant but falls significantly with firm size. The productivity of such investment in terms of innovative sales also indicates diminishing returns, with elasticity of about one-half. For service firms, the productivity of innovation investments is positively correlated to the interaction with scientific research via access to journals and professional conferences. For manufacturing and services, the responsiveness of productivity with respect to share of innovation sales is around 0.1-when the share of innovative sales goes up by 10%, value added increases by 1%, and sales and profits show larger increases of about 2%.

Many productivity-effect innovation studies seem to focus on manufacturing sectors. Among these include Chudnovsky, Lopez, and Pupato (2006) in Argentina and Jefferson et al. (2006) in China who brought evidence on the relationship between innovation and productivity in manufacturing sectors. The result shows that innovative firms perform better than non-innovators in terms of labor productivity during 1992–2001. Their study appears to show that innovation and labor skills seem to be main determinants of firms' productivity because, once firm-specific FE are included, neither group involvement and export activity, nor foreign ownership has a positive impact on productivity. The contribution is noteworthy as it uses panel data and model that takes care of FE and, of course, endogeneity. However, the study doesn't include service firms. The case of Jefferson et al. (2006) in China showed that innovative sales is found to be associated with greater productivity and profitability, mainly in larger, state-owned firms and local government collectives, suggesting that innovation can make big variation in this sector.

The application of GMM to the study of innovation-productivity growth is known to be rare. Bravo-Ortega and Marin (2011) employed

SGMM and showed a strong relationship between per capita spending on R&D and total factor productivity, the relationship being statistically and economically significant even when the quadratic term of the logarithm of per capita R&D and spillovers variables are considered. The magnitude of the estimated R&D elasticity is substantial. It is possible to learn that the long-term elasticity of total factor productivity (TFP) with respect to spending in R&D implies that a 10% increase in per capita R&D spending generates an average rise of between 1.57% and 1.73% in the long-run total factor productivity. This is not only statistically robust but also economically meaningful. Moreover, a number of studies have shown that cooperation of R&D activities among different partners has positive and strong impacts on productivity of partners. Some of the studies that confirm this are Belderbos, Carree, and Lokshin (2006); Kim and Park (2008); Negassi (2004); Okamuro (2007); Barge-Gil (2010); Cassiman and Golovko (2011); Okamuro, Kato, and Honjo (2011); and Capaldo and Petruzzelli (2011).

Another strand of literature is on process or cost-reduction innovation; such studies attempt to analyze the role of innovation as a cost reduction instead of demand-shifting[15] strategy and its positive impact on productivity. For example, Griffith et al. (2006) applied a structural model that describes the link between innovation output and productivity across four European countries (France, Germany, Spain, and the UK), showing that innovation investment intensity has positive and robust impacts on labor productivity. By the same token, van Leeuwen and Klomp's (2006) analysis of the influence of innovation on multifactor productivity growth—based on CIS2 data from 3,000 Dutch firms—found positive effects and also found that the return to innovation investment is sensitive to technological environment.

Summing up, most of the empirical literature reviewed above appears to employ a CDM model and to predominantly use R&D expenditure as an indicator of innovation and, in turn, their impact on firm performance. The focus of most of the empirics appears to be on manufacturing whereas service sectors are not covered as much. None of the reviewed studies disentangle innovation into innovation input and innovation output and compares the effects these indicators have on employment, sales, and productivity. Moreover, studies that use rich panel data and advanced models fail to apply SGMM, which provides consistent and efficient results as it uses levels and differences at a time.

2.3   Contribution of the study

A large number of studies have shown that firm performance can be affected to a large extent by innovation activities. However, most of these studies focus on manufacturing firms whereas the service sector, which supports a greater part of the economy, receives minimal coverage. The present study seeks to address this by providing a comparative analysis of the impacts of innovation input and innovation output on the performance (employment, sales, and labor productivity growth) of manufacturing and service firms. This way, the study seeks to contribute to knowledge in a number of ways.

First, innovation impact studies at firm level seem to use insufficient innovation indicators—in fact, most contributions use R&D expenditure and patents. The two indicators have long been acknowledged—since the pioneering work of Schumpeter (1934)—but have not been able to sufficiently capture the complex nature of innovation. Consequently, implications drawn from limited innovation indicators haven't provided adequate feedbacks on whether the increase, decrease, or inconclusive performance of a firm is attributed to innovation. The present study uses wide-ranging innovation input indicators (R&D intensity, innovation investment intensity, and total innovation intensity) and innovation output (product innovation to firm, product innovations to market and process innovation) and thus provides detailed information on how different innovation indicators would implicate employment performance.

Second, many of the available empirical studies of firm performance effects of innovation use either innovation input or innovation output indicators as explanatory variables where comparative studies using the input and output indicators have not been attempted. Moreover, often times, innovation output indicators are taken as product innovations and process innovations without further disaggregating product innovations into products to firm (firm novelty) and products to market (market novelty). The current study uses firm novelty, market novelty and cost reduction innovations to understand how each of these variables would affect the performance of firms through employment, sales and labor productivity growth. Moreover, this study classifies innovation input indicator into share of R&D (R&D intensity), share of innovation investment expenditure (innovation investment intensity), and share of total innovation investment (total innovation intensity) and estimate the im-

plications these indicators have on firm performance. Such analysis provides detailed evidence and knowledge on whether innovation input or innovation output indicators better explain the performance of manufacturing and service firms.

Third, a large body of empirical literature on firm performance effects of innovation focuses on manufacturing firms while the service sector receives less coverage, partly due to data unavailability and measurement problems in the service sector. Contrary to this, in developed countries (including Germany), the value added share of service firms to total economy is by far greater than the value added share the manufacturing firms contribute to the economy. Under such conditions, a rigorous study of innovation and its impact on service firm performance, in addition to estimating the impacts with which innovation influences manufacturing firms, can contribute immense to existing knowledge. This type of analysis can allows us to better understand the extent to which the performance of service and manufacturing firms responds to innovation and to know the implications of different types of innovation on service as well as on manufacturing sectors.

Fourth, a number of empirical insights that adopt panel data do so using a short panel data set—most often taking three years to investigate the relationship between innovation and firm performance where such data are not able to use SGMM, which requires a minimum of four years. Estimations based on few years and, in particular, those that do not adopt GMM would suffer from the problem of unobserved firm-specific effects, endogeneity, and inconsistent estimations. Further, the effects of innovation on firm performance can better be captured by having sufficient years' data because innovation, by virtue of its nature, requires more years to realize its impact. The present study uses rich innovation data on manufacturing and service firms for the years 2003–2010 and employs a dynamic panel model; hence, it provides detailed knowledge on firm performance effects of different innovations. Such analysis provides robust results that can be replicated in further studies.

2.4   Econometric model and estimation strategy

In this section, I provide the estimation strategy and the model I used to estimate the effects of innovation input and innovation output on firm performance in selected German manufacturing and service firms. The

choice of a model depends, among others, on the nature and type of data as well as on the purpose. This study is based on panel data and, hence, uses panel model that has static and dynamic forms. Following (Baltagi, 2013) and (Wooldridge, 2010), I begin with an estimation of employment growth, one of the firm performance indicators, using a static model as follows:

$$\Delta \ln n_{i\,t} = \rho \ln x_{i\,t}{}' + \ln \phi_i + \ln \varepsilon_{i\,t} \, , \, i = 1,...,N \ \& \, t = 1,...,T \quad (2.1)$$

Where $\Delta \ln n_{it}$ represents employment growth of firm i in year t in logs, ρ is coefficient of x', $x'_{i\,t}$ is a set of variables including innovation input and innovation output that determines employment growth in firm i in year t, $\varepsilon_{i\,t}$ is an independently distributed error term with $E(\varepsilon_{i\,t}) = 0$ for all i and t, ϕ is unobserved firm-specific time-invariant parameter that may be correlated with variable x_i but not with ε_{it}, and $\varepsilon_{i\,t}$ is a time-variant error term of firm i in year t with $E(\varepsilon_{i\,t} \ x_{i\,t}) = 0$ *for all i and t* .

The disadvantage of the static estimation is that it does not include a true state dependence variable, which can have some implications on the employment growth of a firm. Therefore, in order to include the state dependence (lagged dependent) variable, I employ a dynamic panel model. When this is used (Anderson and Hsiao, 1981; Baltagi, 2013; Hsiao, 2003) equation (2.1) will have the following form:

$$\Delta \ln n_{it} = (\rho_1 - 1) \ln n_{i\,t-1} + \rho_2 \ln x'_{i\,t} + \ln \phi_i + \varepsilon_{it} \, , \, i = 1,...,N \,\& \, t = 2,...,T \,(2.2)$$

Where ρ_1 parameter for the lagged dependent variable is n , n_{it_1} is lagged dependent variable, ρ_2 is coefficient of x_i . Equation (2.2) can equivalently be rewritten as:

$$\ln n_{it} = \rho_1 \ln n_{i\,t-1} + \rho_2 \ln x'_{i\,t} + \ln \phi_i + \varepsilon_{i\,t} \, , i = 1,...,N \ \& \ t = 2,...,T \ (2.3)$$

When a set of control variables and year dummy are included in equation (2.3), we get the following estimable model:

$$\ln n_{i\,t} = \rho_1 \ln n_{i\,t-1} + \rho_2 \ln x'_{i\,t} + \rho_3 \ln z'_{it} + \rho_4 \ln yr^*{}_{i\,t} + \ln \phi_i + \ln \varepsilon_{it} \, i = 1,...,N \& t = 2,...,(2.4)$$

Where ρ_3 represents coefficient for control variables, $z^{'}$ are sets of control variables, ρ_4 is the parameter for dummy year, and $yr*$ is year dummy. The dependent variable employment n_{it} is highly likely to be correlated with the time-invariant variable error term ϕ_i. This leads to correlation of the lagged dependent variable n_{it-1}, with ϕ_i as long as n_{it} and n_{it-1} are correlated. Two options are possible to minimize this problem: applying pooled OLS or within estimator. However, when OLS is employed, the coefficient of lagged dependent variable will be inflated, resulting an upward dynamic bias (Hsiao, 1986), eventually creating inconsistent estimation. The use of the within estimator through demeaning techniques will solve the problem of upward bias. Nevertheless, the within estimator will have a downward biased effect (Nickell, 1981) as the sum of its lagged dependent variables tend to have low values. Such problems can be observed even if the lagged dependent variable is not serially correlated with $\varepsilon_{i,t}$. One way to minimize downward bias is to increase the spell as many periods as possible $(T \rightarrow \infty)$, but evidence indicates that even for $T = 30$, the within estimator has a downward bias.

The upward bias panel of the pooled OLS estimator and the downward bias of the within estimator can effectively be solved using first differencing. When this method is applied to equation (2.4), the time-invariant variable error term will be purged, resulting in the following model:

$$\Delta \ln n_{it} = \rho_1 \Delta \ln n_{it-1} + \rho_2 \Delta \ln x^{'}_{it} + \rho_3 \Delta \ln z^{'}_{it} + \rho_4 \Delta \ln yr^{'}_{it} + \rho \Delta \ln \varepsilon_{it}$$

$$i = 1,...,N \,\& \,t = 3,..., \qquad\qquad\qquad (2.5)$$

Provided:

$$E(n_{i,t}\,\varepsilon_{i,t}) = 0 \quad for \quad i = 1,...,N \quad and \quad t = 3,...,T$$

Following first differencing, two forms of GMM can be used: DGMM (Anderson and Hsiao, 1982; M. Arellano and Bond, 1991; Holtz-Eakin et al., 1988) and SGMM (M. Arellano and Bover, 1995; Blundell and Bond, 1998). The two methods not only cancel the time-invariant FE error term but also tend to provide robust estimation. These models provide consistent estimations and are the most advanced econometrics models for panel data. However, each of them has limits.

The DGMM estimator suffers from large finite sample biases when available instruments are weak. In case of persistent series (value of auto-regressive order, ρ is close to unity) and the variance of the fixed-effect ϕ_i increases relative to the variance of disturbances $\varepsilon_{i,t}$, the instruments (lagged levels of the variables for subsequent first differences) are weak (Trufat, 2006). In fact, Blundell and Bond (1998) and Blundell et al.(2002) simulations show that DGMM estimator, in situation of weak instruments, is biased downward in the direction of within group estimator. The bias can be detected by comparing DGMM results with that of pooled OLS and within estimator. We expect consistent DGMM, in the absence of finite sample biases, if it lies between OLS and within estimators. Furthermore, because DGMM uses deep lagged values of the dependent variable to instrument the lagged dependent variable, this works at a cost of reducing sample size. This problem will be enormous if data is unbalanced, which is the case for this study, and if deep lags are to be used. Under such conditions, forward orthogonal deviations or SGMM works well because it subtracts averages of future values instead of lags. System GMM (Arellano and Bover, 1995; Blundell and Bond, 1998) reduces the problem of finite sample biases associated with DGMM due to weak instruments. The DGMM, unlike pooled OLS and within estimator (which can be estimated with panel data of $t = 3$) requires that the longitudinal data should have at least $t = 3$.

The problem of DGMM can be captured by using SGMM, which extends the model by employing moment restrictions of simultaneous system of first-differenced equations and equations in levels. In the first-differenced equations, *lagged level values* of the variables are used as instruments, like in the DGMM estimator. In the levels equations, one uses *lagged differences* as instruments. This estimation strategy requires additional $T - 3$ moment conditions to be valid: $E[\Delta e_{i,t-1}\ (\varepsilon_{i,t} + \phi_i)] = 0$, *for $t = 4, 5,...,T$*, for which the data must have at least $t = 4$. These moment conditions can only be fulfilled when employment change is not correlated with firm-specific effect error term η_i, with the epsilon of the next period, or when the firm does not have knowledge about future shocks (Lachenmaier and Rottmann, 2011).

The decision to use DGMM or SGMM depends on whether the model fulfils requirements of absence of serial correlation and over-identification. The absence of serial correlation of the error terms can be

tested using the Arellano-Bond test of the first order AR (1) and second order AR (2) while over-identification of instruments can be detected by Hansen or Sargan tests. The DGMM or SGMM estimator is consistent if there is no second-order serial correlation in the error terms of the first differenced equation. The null hypothesis that errors are serially uncorrelated is tested against the alternative, and not rejecting the null hypothesis shows the validity of the assumption of no second-order serial correlation. Also the set of instruments used is considered to be valid if there is no correlation between instruments used and error terms. I do not include estimations for sales growth and labor productivity effects of innovation input and innovation output as the procedure is the same as employment growth effects of innovation.

2.5   Data and descriptive analysis

This part is divided into five subparts. The first part provides a description of panel data, after which I present a report of the sampled firms in terms of size, industry classification, and their locations. In the third part, I present the summary statistics of firm performance indicators, including employment, sales, and labor productivity in manufacturing as well as in service firms. Next, I present statistics of innovation input indicators (R&D intensity, investment innovation intensity, and total innovation intensity). Finally, I discuss innovation output variables (product innovation to firm, product innovation to market, and process innovation).

2.5.1   The panel data

This study is based on annual unbalanced survey data drawn from Mannheim Innovation Panel (MIP). The survey data, which covers the years 2003–2010, are conducted by the Center for European Economic Research (ZEW), a think tank organization, in cooperation with the Institute for Applied Social Sciences (INFAS) and the Fraunhofer Institute for Systems and Innovation Research (ISI) of Germany. The survey[16]— unlike most European countries' innovation surveys which follow the CIS guidelines in every three years—is unique as it gather every year's information on innovation of manufacturing and service sectors in a very comprehensive manner, on the one hand, and as the survey contains detail data on innovation input and innovation output indicators on the other. Begun in 1993 and commissioned by the German Federal Ministry

for Education and Research (BMBF), the innovation survey has been conducted on the basis of a CIS framework.

The data contain information on introduction of new products, effects of innovation, services and processes introduced within firms, expenditure on innovation activities, and the degree of success achieved by firms through new products and services, among other things. Moreover, the surveys contain data on employment, sales, and turnover by innovative and non-innovative firms, sales with new products by degree of novelty, financial public support to innovation activities, information sources used for innovation activities, cooperation in innovation projects by type of cooperation partner, use of protection methods for intellectual property, organizational innovation, marketing innovation, and environmental innovation. Moreover, R&D funds disbursed from BMBF are available in the data (ZEW, 2013; Peters and Rammer, 2013).

Unlike the *Oslo Manual* (OECD, 2005) of innovation approach, the composition of MIP changes over time slightly. In the first survey, in 1993, the survey included mining, manufacturing, energy and water supply, construction, and a few service sectors (such as wholesale trade, real estate, computer activities, management consulting, engineering, sewage, and refuse disposal). In the second round, in 1995, the survey became more comprehensive and included retail trade, sale and repair of motor vehicles, renting activities, and business-related services. In the year 2005, construction, retail trade, sale and repair of motor vehicles, real estate, and renting activities were removed due to the low demand for these sectors while the large number of enterprises in the population required a substantial share of the survey's resources. Excluded firms that had responded prior to year 2005 were, however, incorporated in later survey periods. The sample of MIP is stratified by sector, size, region, and the numbers of firms vary by year due to changes in the sector coverage and sector classification schemes. Up until 2008, sector sampling used two-digit code divisions of NACE rev.1, after which rev.2 has been implemented. Change from NACE rev.1 to NACE rev.2 did not, however, bring substantial variation in the classification of sectors. For some groups, three-digit codes of NACE rev.1—which became separate divisions in NACE rev.2—have been introduced.[17]

Table 2.2
Classification of economic activities (NACE) in Germany using two digits

Industry sectors	NACE	Services	NACE
Mining and agriculture	10-14	Distributive services	
Manufacturing		Wholesale	51
Food	15-16	Retail/repairing	50,52
Textile	17-19	Transport/storage/post	60-63, 64.1
Wood/paper/printing	20-22	Real estate/renting	70-71
Chemicals	23-24	Business-related services	
Plastic/rubber	25	Banks/ insurances	65-67
Glass/ceramics	26	Computer/telecomm	72, 64.2
Metals	27-28	Technical services	73, 74.2-74.3
Machinery	29	Consultancies	74.1,74.4
Electrical engineering	30-32	Other business-related services	74.5-74.8, 90
MPO[18] instruments	33	Media	92.1-92.2
Vehicles	34-35		
Furniture/recycling	36-37		
Energy	40		
Water	41		
Construction	45		

Source: Mannheim Innovation Panel (various years).

Based on two digits, NACE rev.1[19] classification firms are grouped into industry[20] (manufacturing) and service sectors. The manufacturing sector has mining and agriculture and manufacturing sectors while the service has distributive and business-related services. The mining, agriculture, and fishery activities, which are basically grouped under primary economic activities, are identified with numbers ranging from 10 to 14 (Table 2.2).

2.5.2   Firm size, classification and location

This part presents a description of the distribution of the number and share of the sampled firms by year, firm classification, and where the sampled firms are located. The data shows that the sample of the survey in each year is disproportional, with large firms having more representa-

tion. Large firms are overrepresented because of the low mortality rate and long-time existence without being changed into other firms. Also, more firms were taken from East Germany as well as firms with a high variety of innovation activities. I draw on a minimum of 10 enterprises per cell and sample all firms that employ 500 or more people. All firms are randomly selected from the CREDITREFORM database, an organization responsible for recording and archiving all businesses that operate within Germany.

The annual surveys were conducted between the months of March and September. Whereas innovation questionnaires sent to small firms were filled out by the managing director of the firm, in large firms, questionnaires were addressed to the head of R&D or a director whose general responsibilities include technology. As a pre-selection of the firms, the survey depends on CIS guidelines and involves only firms that employ 10 or more. However, in Germany, all firms that employ five or more are deemed appropriate for innovation surveys; therefore, in this study, firms that employ at least five are surveyed. Firms that employ more than 1,000 people (which total less than 3% of the whole sample) are not included as these firms with extreme values tend to create biased estimation. Moreover, because innovation surveys in Germany are voluntary and firm mortality is common, especially in small firms, the total sample size in each year can't be expected to be the same. The data is, therefore, unbalanced; and only firms that have been surveyed at least four times are included (Table 2.3). As such, of the surveyed years, year 2008 was found to have more firms whereas the year 2004 has the least number of firms.

Table 2.3
Sample size of manufacturing and service firms by year

Year	Number	Share
2003	1321	10.36
2004	1247	9.78
2005	1640	12.86
2006	1805	14.16
2007	1793	14.06
2008	1898	14.89
2009	1508	11.83
2010	1533	12.02
Total	12745	100

The data further reveal that manufacturing and service sectors are not represented equally. Of the total 12,745 observations (3,124 firms), industry sector—which consists of the manufacturing or processing of food, textile, wood, paper, chemicals, plastics, metal, electromechanical, mining, automobiles, furniture, energy, water, and construction—has 7,861 observations, taking about 63% of the total observations (Table 2.4). Indeed, the shares of the surveyed manufacturing sector have disproportionately been higher than the share of service sector, which consists of trade, transport, banking and insurance, information technology and telecommunication, and related services. Furthermore, a closer inspection of the distribution of the service sectors reveals that the number of observations of the banking and insurance industries has the least in each year compared to other groups of the service sector. With a total of 234 observations, banking and insurance sectors stood the least from the entire share of individual services as well as in each year of service firms. This is followed by information communication technology and telecommunications corporations, where a total of 674 observations were made over eight years (2003–2010). Next come firms engaged in trade, with the total number of observations at 750; then transport, making the total observations 956; and finally other services such as consultancy, media, renting, and related, which take up 2,270 (46.4% of total services, 28.8% of manufacturing, and 17.8% of total observations). It should, however, be noted that if the manufacturing sector were disaggregated into different subsections, certainly the figures in each sector could have

been fewer. Suffice it to say that overall observations of manufacturing sectors outnumbered entire observations of service sectors.

Table 2.4
Industry classification by year

Year	Manufac-turing	Services					
		Trade	Tran.	Bank & Ins.	IT & tel.	Other services	Total
2003	762	87	99	22	87	264	1321
2004	731	90	94	27	75	230	1247
2005	1016	84	147	33	83	277	1640
2006	1111	109	132	36	98	319	1805
2007	1102	108	138	33	93	319	1793
2008	1208	98	137	29	96	330	1898
2009	962	80	105	31	71	259	1508
2010	969	94	104	23	71	272	1533
Total	7861	750	956	234	674	2270	12745

The distributions of manufacturing and service firms do also vary by location. In East Germany, a disproportionately high number of firms have been drawn from both manufacturing and service firms. In particular, 5,020 (64%) of the total 7,861 (3124 firms) manufacturing sectors are located in East Germany while the remaining 2,841 (36%) are in West Germany. Many of the service sectors have also been drawn from East Germany; of the total 4,614 services, 2,865 (62% of the total) are from East Germany (Table 2.5). In both sectors, not only are more manufacturing and service sectors taken from East Germany but also, in each year, the number of both sectors in East part of the country greatly surpassed the number of both sectors of surveyed firms from West part.

Table 2.5
Location of industry

Industry location	Manu-factur-ing	Services					
		Trade	Tran.	Bank & Ins.	IT & tel.	Other services	Total
East	5020	491	593	191	394	1196	7885
West	2841	259	363	43	280	1074	4860
Total	7861	750	956	234	674	2270	12745

The longitudinal data of the sample does vary by firm size and location. Classified into eight[21] different size groups, the survey sample shows that there are more observations throughout East Germany in all firm size categories than the West part of the country. The exception is in the last firm size category, where there is only one firm in West Germany that employs at least 1,000. It is noteworthy to observe that only a few firms employ more than 500, implying that a large number of manufacturing and service firms are of small and medium enterprises (SMEs; Table 2.6). Moreover, the presence of many SMEs in the country could also indicate that such enterprises play a substantial role in building and sustaining the strong economy of the country. However, it is not clear whether a large number of SMEs could innovate in better positions than large enterprises and, hence, contribute to the economy of the country.

Table 2.6
Firm size by location

Firm location	5-9	10-19	20-49	50-99	100-199	200-499	500-999	1,000	Total
East	961	1335	1575	1266	1079	1161	508	0	7885
West	703	998	1308	837	587	363	63	1	4860
Total	1664	2333	2883	2103	1666	1524	571	1	12745

The dominance of SMEs is not only limited by location of industries, it is also noticeable by year (Table 2.7), where in each year the highest number of firms is appeared to be observed in those firms that employ

20–49 people. These firms make about a quarter of all observations (22%). This is followed by firms that employ 10–19, which totals 18% of the overall observations of firms, and then by those firms that employ 50–99. This figure is well within the small business category in European context (i.e., takes 16% of total observations).

Table 2.7
Firm size by year

Year	5-9	10-19	20-49	50-99	100-199	200-499	500-999	1,000	Total
2003	167	249	323	208	151	154	68	1	1321
2004	148	236	283	201	158	159	62	0	1247
2005	226	288	376	261	210	203	76	0	1640
2006	247	354	395	283	235	216	75	0	1805
2007	232	302	414	319	230	218	78	0	1793
2008	247	336	423	332	241	237	82	0	1898
2009	182	279	325	256	219	177	70	0	1508
2010	215	289	344	243	222	160	60	0	1533
Total	1664	2333	2883	2103	1666	1524	571	1	12745

2.5.3 Performance in manufacturing and service firms

Firms engage in innovation activities to achieve one or more of the following: increase employment opportunities, improve sales turnover, scale up productivity, increase efficiency, reduce transaction costs, enhance organizational structure, smooth out marketing strategy, and ensure competitiveness, among others. This section presents a summary of firm performance indicators including employment, sales, and labor productivity (details in Table 2.8).

Table 2.8
Performance in manufacturing and service firms

INN Status	Varia-ble	Manufacturing					Services				
		Obs.	Mean	Std. Dev.	Min	Max	Obs.	Mean	Std. Dev.	Min	Max
INN	EMP	4425	165.54	202.27	5	1000	1814	93.10	148.155	5	990.5
NON-INN	EMP	3436	81.33	127.44	5	987	3070	68.89	116.703	5	925
INN	SALE	4425	3.73	1.01	.051	2.86	1814	1.88	5.09	.093	6.32
NON-INN	SALE	3436	1.99	8.90	.006	3.29	3070	1.06	2.42	.008	4.82
INN	LPR*	4425	.188	.298	.006	6.65	1814	.189	.352	.002	5.15
NON-INN	LPR*	3436	.204	.529	.003	1.90	3070	0.20	0.542	.002	1.39

*In hundreds of thousand Euros; # denotes innovator and NON-INN is non-innovator.

A first firm performance indicator for this study is employment. As indicated in Table 2.8, while an innovator manufacturing sector has on average at least 165.54 employees, the maximum and minimum numbers of employees that an innovator manufacturing firm employs are 1000 and 5, respectively. Innovator service firms, on the other hand, employ a maximum of 990—just 10 employees fewer than the manufacturing firms. However, a striking difference is observed on the mean number of employees where, while a manufacturing sector has on average 165 workers per firm, the service sector has on averages 93 employees—a significantly low figure compared to manufacturing firms. Nevertheless, this is not surprising, given the fact that manufacturing firms are involved in the production of goods which, for various reasons, require many blue-collar workers with low qualifications. The standard deviation of the number of employees in both sectors also shows similar patterns in that although there is a big difference in the distribution of employees in manufacturing and service firms, it is in the former that a bigger variation is observed among the number of employees.

However, it appears that the difference between the mean number of employees in the non-innovator manufacturing and the non-innovator service firms is not very different. This is because although the manufacturing sector has, on average, about 81 employees, the service sector has about 69—a difference of 12. Besides, the data reveal that in the non-

innovator manufacturing and non-innovator service firms, the average number of employees is found to be considerably fewer than that of innovators in both firms.

A second firm performance indicator is that of the sales turnover where, as shown in Table 2.8, an innovator manufacturing firm has an annual sales turnover of 3.73 million euros while its counterpart service firm generates sales of 1.88 million Euros. This provides the information that sales from manufacturing sectors are much higher than that of the sales of the services sectors. However, further scrutiny of the data show that variations in the amount of annual sales among service firms appear to be significantly higher than the variations of sales observed in manufacturing sectors. Indeed, in the manufacturing firm, there is a difference in sales of about 1 million Euros sales, whereas in service firms, the variations in annual sales amount to 5 million Euros. These differences have also shown substantial variances in the minimum and maximum annual sales between manufacturing and service sectors. Whereas half a million Euros of sales have been observed in the manufacturing sector, about a million Euros are generated from the sales of services. A similar pattern is observed in non-innovator industries. Overall, the volume of sales of non-innovator sectors is observed to be lower than that of the sales in innovator sectors, suggesting a positive correlation between innovation activities and sales.

The third firm performance indicator—labor productivity—has also shown useful information. I find that the extent of labor productivity appears to have similar value in the manufacturing and service firms in that, while in the former the value added per unit labor (productivity) is, on average, 0.188 hundred thousand Euros, in the latter sector, the value added per unit labor is found to be 0.189 hundred thousand Euros. Similarly, in the non-innovator manufacturing and service industries, the value added per unit of labor is found to be about 0.2 hundred thousand Euros. Although, on average, innovator industries should normally have better labor productivity outputs than the non-innovator industries, it is in the non-innovator sectors that productivity is found to be higher. However, if one compares the minimum and maximum productivity in innovator and non-innovator industries, it can be seen clearly that innovator firms have more productivity in both manufacturing and service firms. The comparatively extreme values of labor productivity, which are reflected in innovator sectors, might have a significant effect on keeping

the overall labor productivity lower compared to what is observed in non-innovator firms.

2.5.4 Innovation input in manufacturing and service firms

In the previous part, firm size, classification, location, and firm performance indicators have been dealt briefly. In this part I provide summary description of the innovation input in manufacturing and service firms. Innovation input includes R&D expenditure, investment innovation intensity, and total innovation intensity. Analyzing these in both sectors can provide useful information on why innovation input variables might have different intensities in both sectors and what implications these intensities might have on firm performance.

Analysis of the data shows that, on average, manufacturing sectors allocate 0.038% of the capital for R&D, 0.03% for investment innovation and 0.07% for total innovation activities (Table 2.9). Intensity of R&D—which is a measure of the share of money allocated for R&D from the total output of a firm in each year—is an important indicator of the extent of innovation activity at firm level. Indeed, though there is a general consensus that a higher share of R&D is likely to generate and possibly sustain innovation at firm level, no innovation literature provides evidence on what the minimum threshold of R&D intensity should be. With regard to extremes, for R&D intensity, a firm can invest to a maximum of 3.02% of its capital, and the minimum is 0, with a standard variation of 3%. It should, however, be noted that the zero value may mean that a firm doesn't allocate for R&D at all but might undertake other innovation, such as in investment innovation or in total innovation expenditure not accounted for in R&D expenditure.

Investment innovation has taken, on average, only 0.028% of the total turnover in manufacturing industries and 0.038% of the total output in the service industries. These figures—compared to the average amount of investment made for R&D, which is 0.038% in the manufacturing and 0.136% in the services—are significantly lower, suggesting an important difference between investment in R&D and investment in capital innovation activities where much of the innovation expenditure goes to R&D activities. Among other things, investment innovation, also called capital innovation, includes expenditure on buying capital goods and machineries and acquiring or buying technological products, including premises for generating long-run production innovation activities. Investment in-

novation is mainly practiced in large firms whose economies of scale are big enough. Involvement in these areas certainly differs from engaging in R&D activities.

Moreover, it is observed that the mean total innovation intensity is found to be 0.078% in the manufacturing industries and 0.192% in service sectors. The values in both sectors are higher than the average share of R&D intensity, which is 0.038% for the manufacturing and 0.136% for services. Moreover, total innovation intensity in both sectors is greater than that of innovation investment intensity which is 0.028% for manufacturing and 0.038% for services. This, as expected, confirms that the mean total innovation intensity is bigger than R&D intensity and investment innovation intensity. Nevertheless, it is not always the case that total innovation intensity is bigger of a sum of R&D intensity and investment innovation intensity. Sometimes, total innovation could just be either investment made for R&D or investment innovation intensity. It is also possible that total innovation investment is aggregate of R&D intensity, investment innovation intensity, and recurrent[22] innovation intensity (detail in Appendix B1).

Table 2.9
Innovation inputs in manufacturing and service sectors

Variable	Manufacturing (obs.=4425)				Services (obs.=1814)				
	Mean	Std. Dev.	Min	Max	Obs.	Mean	Std. Dev.	Min	Max
R&D INT*	.038	.095	0	3.02		.136	.806	0	4.5
INV INT*	.028	.098	0	4.60		.0385	.166	0	4.9
TOT INT*	.078	.170	0	5.63		.192	.845	0	9.5

*R&D INT, INV INT, and TOT INT respectively refer to R&D intensity, investment innovation intensity, and total innovation intensity.

2.5.5 Innovation output in manufacturing and service firms

Identifying innovator and non-innovator firms is essential to better understand how firms perform. For example, such analysis can help to show whether innovator or non-innovator firm performs well in employment, profit making, or productivity growth. In this part, description

of the innovation output indicators are made with the objective of knowing the number and share of firms that introduced innovation. Accordingly, I find that of the total 12,745 observations, 2,928 of them which introduced product innovation belong to the manufacturing sector, whereas 984 produced a significantly improved product innovation to firm goes to service sectors (Table 2.10). This makes the figure that the total observations of innovating manufacturing and service firms add up 3,912. Usually product innovation is associated with technological innovation such as the production of new machines, equipment, or goods with a view to improve productivity of a firm. Such kinds of innovations are, unfortunately, not common for the service sector, where much of the innovation activities are geared toward cost reduction innovation. Such circumstances might lead only a few service firms to introduce product innovations compared to what the many manufacturing sectors have introduced. Moreover, one can make the crude comparison that for every service firm that introduces product innovations to a firm, there exist nearly three manufacturing firms that do introduce. It should, however, be noted that the total number of manufacturing sectors by far outnumbered the entire number of the service sector, which might explain why the number of manufacturing sectors that have introduced product innovations to firms is greater than the number of service sectors that have introduced product innovations to firms.

Table 2.10
Product innovation to firm by year

Year	Manufacturing			Services		
	Innovator	Non-innovator	Total	Innovator	Non-innovator	Total
2003	270	492	762	111	448	559
2004	307	424	731	101	415	516
2005	406	610	1016	151	473	624
2006	429	682	1111	145	549	694
2007	419	683	1102	146	545	691
2008	454	754	1208	133	557	690
2009	326	636	962	106	440	546
2010	317	652	969	91	473	564
Total	2928	4933	7861	984	3900	4884

A further analysis of the data demonstrates that from a total of 2,252 observations that have introduced product innovations to market (Table 2.11), 1,775 observations (78.82%) belong to innovator manufacturing sectors, and the remaining 477 (21.18%) belong to innovator service industries. This implies that many manufacturing sectors—as with product innovations to firm—have been involved in the generation of product innovation to market. A comparison of the number of manufacturing and service sectors that have introduced new or significantly improved products to firm and to market reveal major differences. This is because, although 2,928 manufacturing firms have introduced product innovations to firm, only 1,775 manufacturing sectors have product innovation to market. This illustrates that the number of manufacturing firms that introduce product innovations to firm is 1.5 times greater than that of manufacturing firms that introduce product innovations to market. Similarly, I find that 987 service industries have introduced product innovations to firm, but for product innovation to market, only 477 services have introduced new products. This again shows that the number of service firms that produce product innovations to firm is twice of the number of service sectors that introduce product innovations to a market over the periods 2003–2010. Year 2008 has the largest number of innovators in both manufacturing and service firms (but should not be a surprise, for the sample size of all firms in 2008 is more than any other).

Table 2.11
Product innovation to market by year

Year	Manufacturing			Services		
	Innovator	Non-innovator	Total	Innovator	Non-innovator	Total
2003	178	584	762	79	480	559
2004	170	561	731	60	456	516
2005	251	765	1016	66	558	624
2006	244	867	1111	59	635	694
2007	253	849	1102	65	626	691
2008	272	936	1208	66	624	690
2009	206	756	962	49	497	546
2010	201	768	969	33	531	564
Total	1775	6086	7861	477	4407	4884

A third category of innovation output indicator is *process innovation*, where of the total 2,096 observations that have introduced cost reduction (process) innovation, 1,627 (which make up 77%) are identified as manufacturing industries while the remaining 469 (which amounts to 33%) are service industries (Table 2.12). Theoretically, cost reduction innovation is predominantly practiced by service sectors because the primary purpose of service industries—as the name intuitively indicates—is the provision of efficient and cost-effective services to customers where these activities require the introduction of techniques, strategies, and mechanisms to fully maintain the sustainable provision of services. If service sectors are not able to generate new techniques, then the performance of such firms could eventually be at risk. Nevertheless, manufacturing firms do not necessarily focus much on introducing process innovations as their major innovation activities are focused on introducing original products or goods at firm or market level, where emphasis is on product innovation.

Nevertheless, the data don't appear to support the superiority of service sectors in the provision of cost reduction innovation as a large number of process innovators are found to be produced by manufacturing firms. This observation could, however, be a reflection of the disproportional sample size of manufacturing and service firms. It has already been mentioned that the sample of manufacturing sectors is larger than the sample of service sectors. To be sure, if the number of service industries that generate process nobility were to be more than the number of manufacturing industries that produced process innovation, then more than 1,010 service firms should have had introduced cost reduction innovation. Another observation is that, compared to product innovations to firm and product innovations to market, the number of manufacturing sectors as well as service industries that introduced cost reduction innovation is small.

Table 2.12
Process innovation to firm by year

Year	Manufacturing			Services		
	Innovator	Non-innovator	Total	Innovator	Non-innovator	Total
2003	145	617	762	36	523	559
2004	161	570	731	67	449	516
2005	210	806	1016	60	564	624
2006	259	852	1111	72	622	694
2007	207	895	1102	68	623	691
2008	245	963	1208	70	620	690
2009	199	763	962	55	491	546
2010	201	768	969	41	523	564
Total	1627	6234	7861	469	4415	4884

Firm performance is not only factored by innovation input and inno-vation output. Other conditions such as whether a firm belongs to a corporate group or is involved in export activity can play roles in increas-ing the competitiveness or otherwise performance of a firm. For exam-ple, a firm that is part of a corporate group can increase a firm's chances of pooling tangible and intangible resources, thereby facilitating infor-mation flows and decreasing transaction costs. Notwithstanding the fact that the benefits of being a partner of a corporate group is an integral part of creating innovation and is essential for effective business opera-tion, this study found that the number of manufacturing and service in-dustries that are part of corporate group is not substantial (Appendix B2). About 31% of the firms that constitutes a total of 3986 observations over the eight years were found to be part of the corporate group. Of this 2,763 observations that make up 35% of the total observations are identified to be manufacturing firms while 1,223 (25%) of the service firms having corporate membership status (detail in Appendix B3). Such a small number could be attributed to the presence of a large number of SMEs, which in many ways may be constrained by financial, knowledge, capital, and related services bottlenecks, which in turn could be a reason many manufacturing and service firms are not part of a corporate group.

Moreover, being an exporter can give a firm the opportunity to learn technologies and knowledge from foreign firms that would increase the

propensity of the firm to innovate and eventually to increase the value added per unit of labor. Firms engaged in export activities are likely to have a comparative advantage in communicating with different multinational and international organizations, can share knowledge and technology, and exchange up-to-date resources. Many more multiplier effects can be observed where the subsequent impacts could result in being more competitive. On the contrary, firms that do not export are less likely to be competitive, performers, or innovators. In fact, the relationship between export and firm performance has long been established in international and industrial economics. Although some studies distinguish between exporting and non-exporting companies and how these factors would affect performance of firms, some analyze the correlation between exporting and firm performance. Economic theory views that exporting firms tend to perform better than those firms that do not export (Castellacci, 2002).

The summary statistics shows that 6068 observations that make about 48% of the total were exporters (Appendix B4) of which 58.52% that count 3551 were identified to be service firms and the remaining 2,517 observations (32%) being manufacturing firms (Appendix B5). This indicates that the share of the service firms that are engaged in export activities are more than the share of manufacturing sectors that do participate in export. In each year, on average, about 444 service sectors are involved in export activities, including in trade, banking and insurance, finance, telecommunications, information communication technology, consultancy, renting, and related services. In the manufacturing sector, however, on average, 315 observations have had export records—this is a figure significantly lower than the services that participate in export.

2.6   Estimation results and discussion

This part, in two sections, provides the dynamic panel estimation results and discussions of the impacts of innovation input and innovation output on firm performance identified by employment, sales, and labor productivity growth. In the first part, I discuss results of the effects of innovation input (R&D intensity, investment innovation intensity, and total innovation intensity) on employment, sales, and labor productivity growth in manufacturing and service sectors (description and measurement of the dependent and explanatory variables are presented in Appendix B6). In the second part, the firm performance impact of innova-

tion output (product innovation to firm, product innovation to market, and process innovation) are interpreted. Each part, therefore, has three models: employment growth, sales growth, and productivity growth.

The lag length of the lagged dependent variable in each model is determined based on the autoregressive estimation, whereas the absence of serial correlations of the time-invariant error terms is tested using the Arellano-Bond test for first order AR (1) and second order AR (2). I also conducted Hansen over-identification for each model to make sure that the instrumental variables used do not correlate with error terms, that they are not over-identified, and that they are valid instruments. For those models that use two-step SGMM a finite sample correction approach (Windmeijer, 2005) is used. Moreover, to identify that the model is biased neither upward nor downward, I check OLS and within (FE) estimator. The criterion is that the estimated model whose coefficients of the lagged dependent variables lie between OLS and within estimator should be proper.

2.6.1 Innovation input and firm performance

In this subsection, I present the estimated results of the impacts of innovation input on employment, sales, and labor productivity growth. The autoregressive estimation shows that the first lag of the dependent variable employment has robust effect on employment growth. Similarly, for the sales and labor productivity growth models, the autoregressive estimation indicates that sale and productivity in their first lag have robust effects on sales and productivity growth, respectively, in which in both models, only the first lag[23] is taken. For the employment growth model, I find that in the manufacturing sector, the coefficient of the first lag of the dependent variable employment growth in two-step SGMM estimator (which is 0.933) lies between the coefficient of lagged dependent variable in OLS (which has 0.976) and in FE estimator (with 0.412). In the service sector, too, the coefficient of the first lag of dependent variable in two-step SGMM has 0.90, which is between the coefficient of OLS (0.970) and FE (0.141).

In the sales growth model of the manufacturing sector, I found that the coefficient of the lagged dependent variable sale in the two-step SGMM (which is 0.768) is between the coefficient of the first lag of sale in the pooled OLS (which is 0.972) and in the FE (within) estimator (which has 0.091). In the service sector, the rho of the lagged dependent

variable sale in the two-step SGMM is found to be 0.783. This value is between the rho of the lagged dependent variable of pooled OLS (0.972) and beta of the lagged variable in the FE model, whose value is 0.074. Observe that although pooled OLS has an upward bias effect, the within estimator has a downward bias; and for the dynamic model to be unbiased and consistent, as Nickell (1981) argued, it must lie between pooled OLS and FE. The estimation, indeed, confirms that the two-step SGMM[24]estimator of the employment and sales growth model in the manufacturing and in services are neither biased upward nor downward; hence, the model is consistent and efficient (Appendix B7).

For the labor productivity model, a test of estimation using Windmeijer (2005) shows that the two-step SGMM estimator is better suited for the data than the DGMM because in the two-step GMM, the coefficient of the lagged dependent variable lies between the coefficients in the pooled OLS and FE estimators. In the manufacturing sector, for example, I found that the coefficients of the first lag of the dependent variable labor productivity in the estimated two-step SGMM (0.368) is between the pooled OLS (0.900) and the FE estimator (-.072). In the service sector, too, the parameters for the lagged dependent variable labor productivity in the two-step SGMM (0.426) is in between the coefficient in the OLS (0.917) and the within estimator coefficient (-.004). Therefore, the coefficient of the lagged dependent variable labor productivity in the estimated two-step SGMM being between OLS and FE in two sectors proves consistency of the estimated model (Appendix B7).

After identifying the two-step SGMM estimator for employment, sales, and labor productivity growth, I interpret results of the estimation. The result reveals that the impact of the first lag of employment on employment growth is positive in manufacturing and service firms, with the level of impact being significant at $p < 1\%$ (Table 2.13). Nevertheless, although previous-year employment has a positive and strong effect on contemporaneous employment in both sectors, it is indeed in the manufacturing sector that the elasticity of the first lag of employment has greater effect on employment growth. This is because, although a 1% rise in the first lag of employment is followed by a 0.88% growth of current employment in manufacturing industries, a 0.78% increase in present employment is evident in the service firms. For the manufacturing firms, the large value of the rho shows that there is an almost one-to-one correspondence between growth of previous-year employment and the

increase in contemporaneous employment. This implies that contemporary employment growth is more responsive to lagged employment in manufacturing than in services. Elasticity of employment in services shows a strong relationship between past and present employment.

Similarly, the first lag of sales growth (L1.SAL) has a positive impact on current sales growth in the manufacturing and services sectors. The level of the impact is substantial at $p < 0.01$ in both sectors, indicating that a growth in the volume of sales in the previous year—regardless of industry type—has both positive and strong feedback in increasing contemporaneous sales. In the manufacturing sector, for example, an increase in sales in the previous year by 1% is followed by a 0.75% increase in the return of sales in the present year, whereas it shows a 0.66% increase in the service sector. The positive and strong elasticity of sales growth with respect to previous-year sales growth in both sectors may, among others, provide evidence on the persistent effects of sales. Moreover, as expected, the first lag of labor productivity has positively and significantly affected current labor productivity growth in manufacturing and service firms at $p < 1\%$ (Table 2.13). The estimation further reveals that a 1% rise in previous-year labor productivity is followed by growth of current labor productivity by 0.37% in manufacturing and 0.42% in service firms. This implies that in the service sector, the elasticity of productivity is higher as long as the coefficient in service sector shows a greater magnitude. This suggests that the sensitivity of labor productivity with respect to previous-year labor productivity is more prevalent in service sectors than in manufacturing sectors.

Furthermore, the impact of R&D intensity, investment innovation intensity, and total innovation intensity as well as their respective first lags on growth of employment, sales, and labor productivity in manufacturing and service firms shows some noteworthy results. In the employment model, the first lag of R&D intensity (L1.FUES) has affected employment growth of the manufacturing firms positively and substantially at $p < 5\%$ and the service sector at $p < 1\%$. However, the impact of current R&D intensity on employment growth is found to be negative but insignificant in manufacturing sectors but positive and robust in service sectors. Innovation-driven firm performance is not an overnight or spontaneous effect; it requires time to use inputs, including R&D expenditure, needs to process inputs into functional form to realize its eventual outcome. This means that, depending on the nature of innovation to be

produced, innovation effects take some time between application of in-
novation and realization of innovation and, therefore, the impacts R&D
intensity can have on employment.

The result that the first lag of *R&D intensity* or *R&D expenditure* has
positive and significant impact on employment growth in manufacturing
as well as in service firms confirms the behavior of innovation.[25] The
elasticity of the first lag of R&D intensity with respect to employment
growth in the manufacturing sector shows that a 1% increase in the
share of Euros invested in R&D activities in the previous year leads to a
0.11 % growth in current employment; in service firms the same amount
(1%) has resulted in a 0.08% growth of employment. In both sectors, the
relationship between increase in past expenditure in R&D and current
employment growth appears to be strong and reinforcing. A comparison
of the employment growth with respect to the previous-year R&D ex-
penditure shows that the manufacturing sector is found to be better than
the service sector. However, contemporaneous R&D intensity has no
significant influence on employment growth in the manufacturing sector.
This is not the case in services where the share of current expenditure on
R&D has not only positive but also robust impacts on employment
growth, with the level of the effect being strong at $p < 0.01$. This may
indicate that service sectors do not seem to take time to realize that in-
novation (R&D expenditure) effects or those effects of innovation activ-
ities (explained in terms of R&D expenditure) are automatic.

In the sales growth model, like in the employment growth model, the
share of R&D expenditure of the previous (L1.FUES) has a positive im-
pact on current sales growth in the manufacturing and service industries
with the extent of impact being robust at $p < 1\%$. Nevertheless, a slight
difference is observed between employment growth and sales growth
effect of the first lag of R&D intensity, where in the former the impact is
robust at 5% in the manufacturing sector and is significant at 1% in the
service sector. Previous-year R&D intensity and its positive influence on
contemporaneous sales growth in manufacturing and services appear to
confirm the expectation, but I find them to be against the insights of Del
Monte and Papagni (2003), who found an insignificant and negative im-
pact. Further scrutiny reveals that although the impact on sales growth
of R&D intensity in both industries is found to be robust at $p < 1\%$, it is
indeed in the service sector that the elasticity of sales growth with respect
to R&D expenditure is more responsive—a 1% increase in the first lag

of the share of R&D expenditure in the service sector is followed by 0.36% growth in sales growth while the same amount of R&D results in a 0.30% increase in the manufacturing.

With a slight variation from the first lag of R&D intensity, current R&D intensity (FUES) does have a positive and substantial effect on sales growth in manufacturing sectors but only positive effects in services industries. The effect that contemporaneous R&D intensity has insignificant effects on sales growth in the service sector may indicate that the time between investment in R&D and its realization on sales growth could be too short and, accordingly, the effect could end up being not robust. Put differently, R&D expenditure may require some time to effectively realize its impact. Certainly, there is a time gap between production of goods and services and the sale of these products in market (production and sale can't be undertaken simultaneously) in the service sectors. Under such circumstances, present R&D intensity intends to increase first production of services in the service sector and not necessarily sales or marketing of services. Sale of the services may then be realized in the following year, making the impact on the present year not really meaningful—or at least not as important as one would expect.

Moreover, I find that expenditure on R&D has a positive role in enhancing labor productivity in both sectors. More specifically, in the manufacturing sector, while the first lag of R&D intensity (L1.FUES) and current R&D intensity (FUES) have impacted productivity of labor at $p < 5\%$ and only positively, respectively, in case of service sectors, both the first lag and contemporaneous R&D intensity do affect labor productivity not only positively but also with considerably at $p < 1\%$. Nevertheless, the extent of the impact of the first lag on labor productivity has different effects in that the elasticity of productivity in services is more than the elasticity of productivity growth in manufacturing industry (a 1% increase in euros invested in previous year R&D increases labor productivity of services sectors by 0.28% and that of the manufacturing firms by 0.20%). Current R&D intensity has positive feedback on the productivity of labor in services at $p < 1\%$ but is not so strong in manufacturing industries.

A second indictor of innovation input is *investment innovation intensity or investment innovation expenditure* where its impact on firm employment, sales and labor productivity growth provides important insights in manufacturing and service firms. With respect to employment growth, the impact

in the manufacturing sector is identified to be significant at p < 1% and in the service industries at p < 5%. Because investment innovation covers expenditures on capital innovation activities, and because the effects of such activities require more time to realize outcomes, the result that the first lag has indeed contributed a strong and positive impact on employment growth in two sectors strongly conforms to the persistent behavior of innovation. The case with the implications of current investment innovation on employment is different because whereas the influence of present investment innovation expenditure leads to an increase in employment in the service sector, it has negative implications in the manufacturing sector. This may imply that in the manufacturing sector, the realization of capital innovation intensity (as an indicator of innovation and its impact on employment) is not automatic and is time dependent. The negative impact of current investment innovation intensity could also be explained by costs associated with buying capital goods, which tends to reduce labor demand. This will decrease employment opportunities because there is a likely effect of shifting resources from hiring new employees into investment in capital innovation activities. It could also be due to the introduction of capital or investment innovation activities, which requires hiring of highly specialized experts who are fit to new technologies and, at the same time, firing low-skilled laborers who could not afford to work in the new technology-supported environment. Unfortunately, it is not possible to know the kind of skills employees have or the quality of employees of manufacturing industries.

The elasticity of sales growth with respect to investment innovation shares the behavior of the employment growth model in that the first lag of investment innovation intensity (L1.INVS) has a positive and considerable impact on sales growth in both firms. A firm that allocates funds for the acquisition of capital goods in the previous year does increase the sales growth of the current year. Moreover, whereas present investment innovation has impacted sales growth in manufacturing at $p < 1\%$ it is only positive in the case of service industries. Moreover, I find that expenditure on R&D and expenditure on investments or capital innovations have similar patterns on performance of sales in manufacturing industries as well as in service sectors. This shows that R&D intensity and expenditures made to increase capital goods and services not only seem to go in the same direction but also have affected sales growth with almost the same magnitude.

Investment innovation does also have a slightly different impact on labor productivity compared to the way investment innovation intensity affects productivity. Indeed, previous-year investment on capital innovation has spurred output per unit of labor in the manufacturing and services with the level of impact being substantial at $p < 1\%$. The fact that the first lag of investment in capital innovation activities consistently contributes greatly to the two sectors indicates that the persistent nature of innovation might be strong enough to affect current labor productivity. However, it is not possible to be sure whether the deep lag lengths of investment innovation could have similar effect as the study is limited to only the first lag length. There is also a big difference in the two groups of industries in the ways in which labor productivity is being affected—that whereas a 1% increase in the first lag of investment innovation has increased productivity of labor by 0.48% in the manufacturing, it does so to services by 0.72%. Therefore, productivity of labor with respect to previous investment innovation is more responsive in the service sector than in manufacturing industries. Current investment innovation has modest effects on labor productivity in both sectors. Indeed, although capital spent on investment innovation has encouraged productivity of labor of manufacturing and service sectors, the level of encouragement is not robust in either the manufacturing or service firms.

A third innovation input indicator for this particular study is *total innovation intensity* or *total innovation expenditure* (IAS). As was found for the implications of R&D intensity (FUES) and total investment innovation (INVS), IAS has useful implications on firm performance. I have found that the first lag of total innovation intensity (L1.IAS) has positive and robust impacts on employment in the manufacturing and service industries at $p < 1\%$. Total innovation expenditure includes R&D expenditure, capital innovation expenditure, and recurrent innovation expenditure, including money invested or allocated to training, wages, social services (health services), allowances, and related activities. Investment in such activities does not necessarily add value or productivity to a firm instantly; it has a tendency to increase the return of employment in future. This is what has happened in this study—in the manufacturing industry, a 1% rise in previous year total innovation spurred employment growth by a 0.20%, and it resulted in a 0.22% increase in service firms. This appears that elasticity of L1.IAS with respect to employment growth in service

sector is slightly higher than that of the elasticity of total innovation intensity with respect to employment in manufacturing sector.

On the contrary, current IAS has negative effects on employment growth in both firms. In particular, in service sectors, the effect is not only negative but also robust. This is in sharp contrast to the implications of current R&D intensity (FUES), which has positive effects on employment growth in both sectors, and current investment innovation intensity (INVS), which has positive effects on employment growth in services. In the service sector, as feedbacks of current R&D intensity and current investment intensity on employment growth are positive, and these innovations are part of total innovation expenditure, it is reasonable to expect that the discouraging impact on employment growth of total innovation expenditure can be attributed to recurrent innovation expenditure, which is, indeed, part and parcel of total innovation. Recurrent innovation has the tendency to shift resources from productive activities into expenses that do not necessarily add value or provide direct impact. As such, if the amount of recurrent innovation expenditure is significant compared to R&D expenditure and investment innovation, surely much of the total innovation expenditure will be contributed by recurrent innovation. This tends to suppress the impact of current total innovation on employment growth; hence, it will have negative feedback.

Total innovation intensity also plays significant roles in sales growth. More importantly, I have found that preceding-year total innovation intensity (L1.IAS) has both positive and robust effects on sales growth in manufacturing and service industries. On the contrary, present expenditure on total innovation—unlike current R&D intensity and present investment innovation intensity—has a negative effect on sales growth in both firms. This could be explained by the presence of recurrent expenditure, including outlays on salary, training, health provision, and related social services that are part of total innovation. This expenditure has the potential to squeeze resources and, thus, tends to decrease overall sales growth. However, today's negative effects of recurrent innovation expenditure can have positive effects sometime in the future.

With respect to labor productivity, total innovation expenditure has discouraging effects in the manufacturing and service sectors. The negative influence is not significant in both sectors, however. Recall that total innovation includes expenditure on R&D, on investment innovation, and on recurrent items such as salary, training, and related social services.

As a matter of fact, expenditures to employ individuals, train staff to equip the necessary skills required by the organization, and to provide other services to the employees can shift resources from productive areas into unproductive areas for a while where such conditions tend to affect labor productivity negatively. However, innovation expenditure on recurrent activities would certainly have a positive effect on productivity in the long run; what is invested today to employ or train experts can provide a return in the future. Indeed, the negative impact of current total innovation on labor productivity in manufacturing and services could emanate from the presence of a high share of recurrent innovation expenditure. Moreover, it is also interesting to note that whereas IAS has a discouraging effect on labor productivity growth in both firms, the effect on productivity of the first lag of total innovation intensity (L1.IAS) has not only positive but also substantial effects in both firms. This implies that investments in total innovation in the previous year as well in the current year have different effects on the performance of firms, explained through productivity of labor.

Two more variables—being a member of corporate group (MEM) and exporter (EXP) of goods and services—are used as control variables of firm performance (employment, sales, and labor productivity growth) in both industries. Evidence shows that firms engaged in export activities tend to increase firm size, sales, and productivity in better positions than firms that do not export (Alvarez and López, 2005). For example, Pellandra (2013) found that exporting leads to an increase in employment of low-skilled workers but has no significant effect on employment of high-skilled workers. Wagner's(2012)[26] analysis of the links between international trade (exports and imports) and dimensions of firm performance (productivity, wages, profitability and survival) based on review of empirical literature that consists of recently published papers in manufacturing or services industries provides very useful insights. He found a big picture that exporters and importers are more productive than non-exporters and non-importers. He further showed that exporters and importers were more productive in the years before they started to export or import (self-selection); the number of export markets served increases with firm productivity, and that exporters to more developed economies have superior *ex ante* productivity levels than non-exporters and firms exporting to less developed countries. The present study shows that a firm engaged in export activities has positive impact on

employment growth in manufacturing sectors. The effect is robust, and the more a firm is engaged in export activities, the more the likely that it will increase employment, supporting the economic theory that export—via increasing labor demand—improves firm performance.

In the service industry, however, export has not had a robust influence on employment, but the impact is found to be positive. In Germany, automobiles, pharmaceuticals, and electronic products are the leading exports of manufacturing firms, whereas in the service sectors, financial, communication technology, banking, and engineering consultancies are the dominant exports. Indeed, Germany is known to be one of the world leaders in manufacturing and exporting high-tech products where such features could help firms to employ a significant share of the labor force and, therefore, to increase employment in the manufacturing sector as compared to services. Automobiles such as Porsche, BMW, Mercedes Benz, and Volkswagen, just to mention a few, are among the leading products and exports of Germany. Moreover, being part of a corporate group or having sister companies within Germany has spurred employment growth at $p < 1\%$ in the manufacturing and at $p < 5\%$ in the service sector, respectively. This indicates that having business networks increases chances of resource exchange, including employee pooling, raw material exchange, and financial collaborations, and simultaneously reduces transaction costs, enhances firm productivity, and will eventually have tendency to increase employment of a firm.

The two variables—corporate membership and exporting—also have considerable impacts on sales growth over the years 2003–2010 in both sectors. However, the extent of the impact differs between the manufacturing and service sectors. In the manufacturing sector, for example, a firm that exports goods and services has increased growth of sales by 0.25%—a firm engaged in export activities, regardless of the kind of export, tends to spur sales by 25%. Exports not only increase the chances of improving selling more services, they also increase competitiveness, help gain knowledge from foreign firms, provide technology and knowhow exchanges, keep abreast of updated issues regarding trade, and pool human resources. Export has definite multiplier effects that keep firms as efficient as possible. The results confirm this.

Table 2.13
Two-step SGMM estimates for innovation input-driven firm performance

Explan-atory variables	Employment growth		Sales growth		Labor productivity growth	
	Manufac-turing	Services	Manufac-turing	Services	Manufac-turing	Services
	ρ (sta. err)	ρ (sta. err)	ρ (sta. err)	ρ (sta. err)	ρ (sta. err)	ρ (sta. err)
L1.EMP	.883 (.015)***	.781 (.020)***				
L1.SAL			.725 (.026)***	.660 (.013)***		
L1.PROD					.368 (.024)***	.426 (.015)***
L1.FUES	.118 (.054)**	.085 (.017)***	.309 (.095)***	.368 (.033)***	.209 (.101)**	.280 (.019)***
FUES	.080 (.061)	.210 (.020)***	.330 (.134)**	.008 (.033)	.048 (.099)	.212 (.023)***
L1.INVS	.304 (.065)***	.061 (.029)**	.338 (.095)***	.458 (.058)***	.489 (.092)***	.723 (.036)***
INVS	-.052 (.063)	.010 (.051)	.754 (.121)***	.003 (.065)	.126 (.091)	.016 (.036)
L1.IAS	.208 (.055)***	.220 (.015)***	.391 (.073)***	.400 (.028)***	.275 (.077)***	.377(.015)***
IAS	-.020 (.048)	-.090 (.016)***	-.756 (.051)	-.223 (.160)	-.626 (.509)	-.046 (.031)
EXP	.100 (.013)***	.019 (.018)	.250 (.031)***	.118 (.035)***	.092 (.025)***	.279 (.028)***
MEM	.125 (.019)***	.044 (.020)**	.445 (.051)***	.639 (.032)***	.276 (.023)***	.254 (.032)***
Year dummy	included	included	included	included	included	included
AR (1)	z = -4.81 Pr > z = 0.000	z = -3.33 Pr > z = 0.001	z = -2.29 Pr > z= 0.022	z = -4.71 Pr > z = 0.000	z = -2.78 Pr > z = 0.005	z = -4.95 Pr > z = 0.000
AR (2)	z = 0.08 Pr>z = 0.934	z = 1.62 Pr > z = 0.104	z = 1.51 Pr > z = 0.132	z = 1.78 Pr > z = 0.075	z = 1.61 Pr > z = 0.106	z = 0.51 Pr > z = 0.609
Hansen overid.	x^2 (125) = 41.18 Pr > x^2 = 0.153	x^2 (156) = 154.22 Pr >x^2 = 0.525	x^2 (122) = 128.3 Pr > x^2 = 0.330	x^2 (91) = 77.09 Pr > x^2= 0.851	x^2 (122) = 143.33 Pr > x^2 = 0.091	x^2 (122) = 111.12 Pr > x^2 = 0.750
Obser-vations	4175	2472	4175	2472	4175	2472
Firms	1802	1099	1802	1099	1802	1099

Standard errors in parentheses, **$p < 0.05$, ***$p < 0.01$

In the service sector, being an exporter increases the chances of sales growth by 0.11%, a figure much lower than that of the growth in the manufacturing sector. Under such circumstances we would observe that the extent to which sales growth responds to exports in the manufacturing sector is more than the effect exports had on services' sales growth, as evidenced by a larger coefficient in manufacturing industries. Moreover, a firm that networks with other companies increases the opportunity of having resources such as financial, employee human, material, consultancy, and knowledge transfer. For example, Musso and Schiavo (2008) show that access to external financial resources has a positive effect on the growth of firms in terms of sales, capital stock, and employment. In this study I find that sales growth in the services sector has more sensitivity with respect to being a member of corporate group, suggesting that being an exporter and part of a corporate group have different implications on sales growth in manufacturing and service sectors.

Memberships in a corporate group and being an exporter have also had great implications on labor productivity. More importantly, export as a control variable has greatly contributed to growth of labor productivity of the manufacturing and services, with the level of contribution being robust at $p < 1\%$. Being an exporter of goods and services has increased output per unit of labor growth of manufacturing firm, on average, by about 0.09% and in the services sector by 0.27%. This implies that elasticity of productivity of labor with respect to export in the service sector is more than the productivity of labor in relation to export in manufacturing sectors or in manufacturing and service sectors. Indeed, the responsiveness in the services sector is three times the responsiveness of the productivity in manufacturing firms. These indicate that the export of services from service firms, such as in banking, insurance, finance, telecommunications, and consultancy, have spurred output per unit of labor better than exports obtained from manufacturing sectors.

Firms that are members of corporate groups or enterprises within Germany tend to increase the productivity of labor compared to firms that do not have any form of membership or have not had any legal network with other enterprises. The positive effect on productivity of labor of business membership is uniform across manufacturing and service firms, with the level of impact being substantial at $p < 1\%$. There is, however, a difference between the elasticity of labor productivity with respect to membership of corporate group in manufacturing and ser-

vices, to which, if and when a firm is part of an enterprise, it increases productivity by 0.27% in manufacturing, whereas it is 0.25% in service industries. A comparison of the impact of enterprise membership with that of export on productivity of labor reveals similar patterns as well as differences. Whereas both firm membership and exports have positive and considerable effects on improving the growth of productivity in manufacturing and services, the level of impact is different; whereas productivity with respect to export is 0.09% in the manufacturing sector, the elasticity of productivity in response to corporate membership is 0.27% in same sector. This implies that membership in the enterprise group has more impact on increasing productivity in the manufacturing sector—more productivity than what an exporter can induce in same sector; productivity with respect to enterprise membership (0.27%) is three times better than productivity in response to export (0.09). In the services sector, however, export has more impact on productivity than does membership.

To sum up, the estimation results of the employment, sales, and labor productivity growth effects of innovation input have shown a number of insights. I have found that the lag lengths of the dependent variable in employment growth and the sales growth model are determined by using the autoregressive model. Furthermore, results indicate that the growth models, which are estimated using SGMM, are unbiased. In particular, in the employment growth model, a test of the absence of serial correlations of the error terms using Arellano-Bond test for first order AR (1) and for second order AR (2) shows that there is no autocorrelation of the idiosyncratic error terms. This is because AR (1), with $p = 0.000$ in manufacturing and services, as well as test of AR (2) with $p = 0.934$ in manufacturing and $p = 0.104$ in services, shows an absence of serial correlations because $p > 0.05$ for both sectors. Besides, the Hansen over-identification test with $p > 0.05$ in both sectors proves that the number of instruments used is not over-identified and is valid; hence, the estimated employment growth model, which employs SGMM, is unbiased, consistent, and properly specified.

Similarly, in the sales growth model, the Arellano-Bond test in its first order AR (1) reveals that $p = 0.022$ in manufacturing and $p = 0.000$ in the services are within the required threshold because p < 0.05, in the specified model, are well within the required level. A second order test AR (2) shows $p = 0.132$ in the manufacturing and $p = 0.075$, both with

$p > 0.05$, proving that there is no serial correlation of idiosyncratic error terms. Further, the Hansen test of over-identification test with $p = 0.330$ in the manufacturing and $p = 0.850$ in the services, where both sectors having $p > 0.05$ indicates that the numbers of instruments estimated using xtabond2 are not over-identified. The test of serial correlations and over-identifications, therefore, shows that the innovation input-driven sales growth model is properly specified.

For the labor productivity model, the specified model is also found to be efficient and consistent. It is consistent because the p-values of the first order Arellano-Bond estimates AR (1) and second order AR (2) in the manufacturing sector are be 0.005 and 0.106, respectively; this is within the required range of the dynamic panel estimation. In the service sector, AR (1) has $p = 0.000$ while AR (2) has $p = 0.609$. In both sectors, the AR (1), with $p < 0.05$, and AR (2), with $p > 0.05$, shows that the estimated model is well within the required value of the properly specified model. This indicates that the null hypothesis that idiosyncratic error terms are serially uncorrelated is accepted. Moreover, the Hansen over-identification tests in the manufacturing were $p = 0.091$ and in services were $p = 0.750$, all of which are more than the required threshold of $p > 0.05$, confirming that the numbers of instruments used are not over-identified (Roodman, 2009). This implies that the instruments used are valid, that there is no correlation between instruments and error terms, and that the two-step SGMM model is properly specified.

2.6.2   Innovation output and firm performance

In the previous part, I discussed the estimated results of the impacts of innovation input on employment, sales, and labor productivity growth in manufacturing and service firms using two-step SGMM. The three innovation input indicators—R&D intensity, investment innovation intensity, and total innovation intensity—are constructed by taking their expenditure share from the corresponding output of a firm. As such, innovation input indicators are measured quantitatively, and their effects on firm performance have therefore been analyzed through a quantitative approach. However, quantitative indicators of innovation are not sufficient to analyze firm performance.

Qualitative innovation indicators and analyzing their implications on firm performance have increasingly become hotspots in innovation impact studies. In this part, I discuss the impacts of innovation outputs[27]

(product innovation to firm, product innovation to market, and process innovation) on employment, sales, and labor productivity growth. Each of the innovation output indicators has binary value (either product innovation is introduced to firm or not, product innovation is introduced to market or not, and process innovation is introduced or not). The contribution of the essay, in this regard, lies in disentangling product innovations into product innovation to firm and product innovation to market, which many other studies fail to take into account. In this part, like in the previous section, three models are presented: the employment, sales, and labor productivity growth, all based on innovation outputs. Moreover, using the autoregressive model, the lag lengths of all the explanatory variables are identified to be one. It is not possible to use deeper lags because of the unbalanced nature of the data and the extreme reduction in sample size. Therefore, the lists of variables that are used as explanatory include (a) the first lag of product innovation to firm (L1.FPD), (b) first lag of product innovation to market (L1.MPD), and (c) first lag of process innovation (L1.REK) and their corresponding contemporary values. In addition, two control variables; corporate membership (MEM) and export (EXP) are used as control variables (description and measurement of innovation output indicators in Appendix B8).

The first estimated model is that of the employment growth where the two-step SGMM is found to be appropriate. A test of the specification of this model shows that the coefficient of the lagged dependent variable in the two-step SGMM lies between the coefficients of the lagged dependent variable in the OLS and in FE estimators. I find in the manufacturing sector that the parameter of the lagged dependent variable in two-step SGMM (0.976) is between the lagged coefficient in OLS (0.412) and in the FE estimator (0.933). In the service sector, the first lag of employment in two-step SGMM has a coefficient of 0.903, in the pooled OLS 0.970, and in FE 0.140. Therefore, in the manufacturing and service sectors, the coefficient of the first lag of employment is between OLS and FE, proving that the model is unbiased (Appendix B10).

The two-step SGMM estimator is also found to be appropriate for the sales growth model because in the manufacturing sector, the coefficient of the first lag of the dependent variable sales growth (0.768) is between the coefficients of the OLS (0.972) and FE (0.091). Moreover, I find a similar result in service sectors (Appendix B8). For the labor productivity model, too, the two-step SGMM is found to be appropriate.

It is appropriate because the coefficient of the lagged dependent variable in two-step SGMM (0.494) in the manufacturing sector is between the coefficient of the lagged dependent variable in OLS (0.899) and the coefficient in the FE estimator (-.076). In the service sector, too, the estimated coefficients of the lagged dependent variable in the two-step SGMM is 0.726, lying between the coefficients of pooled OLS, which is 0.919, and of the FE (within) estimators, which is -0.004. These indicate that estimating the impacts on labor productivity growth of innovation output using two-step SGMM is neither biased upward nor downward and is free from Hsiao (1986) or Nickell (1981) bias.

Following the identification of the appropriate model, I analyze the impacts of innovation output (product innovation to firm, product innovation to market, and process innovation) on employment, sales, and labor productivity growth. The estimation shows that preceding-year employment has a positive and robust impact on current employment growth. The positive and enormous impact indicates that an increase in employment in the previous year tends to increase the likelihood of employment in the present year; and at the same time, a decrease in employment of the previous year decreases the chances of employment of the current year. This is observed to be the case for the manufacturing and service sectors, where a 1% increase in the first lag of employment is attributed to a 0.93% increase in current employment growth in the manufacturing sector and a 0.90% growth of present employment in the services sector (Table 2.14). This demonstrates that the elasticity of employment growth with respect to the first lag of employment is almost the same for the manufacturing and service firms when innovation outputs is used as predictor. In the innovation input-driven employment growth, however, I have found that the responsiveness of current employment growth with respect to previous-year employment was 0.88% in the manufacturing and 0.78% in the service firms.

Moreover, as anticipated, an increase in previous-year sales growth contributes positively and immensely to growth of current sales in both sectors. Surprisingly, the first lag of sales growth—apart from having positive and robust implications on current sales growth in manufacturing and services—has almost identical impacts on the responsiveness of current sales growth in both sectors. For example, in the manufacturing industry, a 1% increase in the sales volume in the preceding year is attributed to a 0.76% growth of current sales while the same amount (1%)

of growth of previous-year sales leads current sales of the services sector to grow by 0.78%. The elasticity of current sales growth of service sector with respect to the previous-year sales only slightly outweighs that of the responsiveness of current sales of manufacturing firms.

With respect to labor productivity growth, the result reveals that current labor productivity in manufacturing and service firms are positively affected by preceding-year labor productivity where the extent of impact is found to be substantial at $p < 1\%$ (Table 2.14). More importantly, though the effect has strong positive impacts on both industries, it is in the services sector that the influence is more elastic. This is because, whereas a 1% increase in the amount of preceding-year labor productivity is responsible for a 0.72% growth of current output per unit of labor in services, a unit percent increase in previous-year labor productivity growth has resulted in approximately half (0.49%) the growth of present labor productivity in manufacturing firms. This implies that although a firm that increases productivity in the previous year tends to spur labor productivity of the present year in both sectors, it demonstrates that a firm that has experienced negative productivity growth in the previous year would have the same reduction effect in both sectors. This is consistent with the results of many of the innovation-productivity relationship studies, including the works of Crepon et al. (1998).

Product innovation introduced to firm—one of the innovation output indicators—affects *employment growth* positively, both in the manufacturing and service industries. However, the extent of impact differs between the two sectors. In the manufacturing firms, the introduction of product innovation to firm has affected employment growth at $p < 0.1$ and in services at $p < 0.01$, showing that service sectors are more elastic to innovation produced to firm than manufacturing sectors. As such, it is evident that if and when a service firm introduces product innovation to firm, then the employment growth of the very same firm will be spurred by about 0.04%, whereas that of the employment of the manufacturing industry will grow by 0.01%. However, preceding-year product innovation to firm (L1.FPD) has a positive but insignificant impact on employment in both the manufacturing and service firms. This might indicate that persistent effects of product innovation at firm are not strong enough to have great implication on the employment performance in the following year. Probably, innovation produced to firm has become obsolete quickly and therefore can no longer greatly influence labor demand of firm.

It is also interesting to observe that product innovation to firm has positive impacts on *sales growth* in both industries, although the level of impact differs between manufacturing and services. Specifically, while preceding year product innovation to firm (L1.FPD) has enormous influences on sales growth at $p < 1\%$ in manufacturing sectors, service sectors sales growth has not been significantly impacted by preceding-year product innovation to firm. Indeed, the introduction of significantly improved, original or new innovation to a firm in the preceding year—and not to a market—has helped manufacturing sectors to increase the sales of goods and services, which is not the case in service sectors. The elasticity of sales growth in the manufacturing sector with respect to the first lag of product innovation to firm is substantial because a firm that introduces product innovation tends to beef up the sales volume of the same firm by about 0.06%. Compared to the first lag, current product innovation to firm has positive and strong impact on the probability of increasing sales volume in manufacturing and services. Especially in manufacturing firms, the effect appears to be strong at $p < 0.01$, though it is also noteworthy that the implications of the impact in the services sectors are robust at $p < 0.1$.

Product innovation to firm has also encouraging influence on firm performance through *labor productivity* in both firms. Indeed, the first lag (L1.FPD) and current (FPD) product innovations to firm have impacted labor productivity in manufacturing as well as in service sectors at $p < 5\%$. What is more, a comparison of the elasticity of productivity of labor in manufacturing and service sectors reveals that a 10% increase in the production of new or original goods and services to firm has resulted in a 5% growth of productivity of labor in the services sector whereas the change innovation brought to labor productivity is 3% in the manufacturing sector. As a matter of fact, service sectors employ more white-collar workers whose education and skill are on par with available technology, whereas manufacturing sectors employ many blue-collar workers whose skills are mostly incompatible with technology. Under such circumstances, it is reasonable to expect that the productivity of a skilled labor force, *ceteris paribus*, is better than those who are not skilled. This is because the former, with better knowledge inputs through formal education, are able to innovate and generate new ways to directly or indirectly improve the performance of a firm. This condition tends to have a greater effect on increasing productivity in service firms than in manu-

facturing firms. The result confirms this. In the case of labor productivity, current product innovation to firm has a positive impact on productivity in both sectors where the level of impact is robust at $p < 5\%$ in the manufacturing industry and is insignificant in service sectors.

The second indicator of innovation output is *product innovation to market*, where although it has positive influence on the employment growth in manufacturing and service sectors, it is different if we examine how this innovation affects the demand for and supply of labor (employment) growth at firm level. For example, I find that current product innovation to market has contributed to employment growth positively and significantly in the manufacturing sector but has a negative and insignificant effect on employment in services. In the manufacturing sector, present product innovation to market has, to a large extent, been responsible for the increase in employment growth where the introduction of product novelty at market increases the probability of employment in the same sector to grow by 0.01%. The negative role of current product innovation to market in employment growth in the services sector could be a result, of the phenomena that the introduction of new products in form of goods and services in the market could increase market outlets, coverage, and efficiency of service sectors (such as telecommunications, trade, finance, banking and insurance). The progress in the introduction of new products into market increases efficiency of distribution, accessibility and provision of services. The efficient provision of services backed by new technologies has the greater tendency in decreasing the total number of employees who work in the service sector, especially the blue-collar people, who are less skilled. Specifically, employees who do not have the required training, knowledge, and competency with up-to-date technology are likely to be indirectly affected and laid off from the organization in which they work; hence, this tends to decrease the number of employees who work in the service sector.

The first lag of product innovations to market (L1.MPD) has also a lowering effect of employment in the service sector where the influence is not only negative but is also considerable. Indeed, a large number of layoffs in the banking and related service sectors can, among others, be attributed to the introduction of service novelty in the market—a phenomena that such innovation has a substitute of the labor force instead of being a complementary. Furthermore, a useful distinction to observe from this result is that although the first lag and current product innova-

tion to a firm have positive effects on employment growth in the service sector, the first lag and present novelty to a market is negative in the same sector. This implies that product innovations to a firm and to a market have different implications on the supply and demand of labor (employment) conditions. Unfortunately, it is not possible to know whether the increase in employment due to product innovations to firm or decreases in employment due to product innovation to market are for low-skilled or high-skilled employees. It is hardly possible to identify the quality of employment as well as the kinds of expertise employees have unless there is data on the level and specialization of qualifications.

The introduction of product innovations to market in the previous year as well as in the current year has brought considerable influences on *sales growth* in the manufacturing sector. However, the first lag of innovation to market is not as strong as the first lag of innovation to firm in affecting the sales growth of manufacturing industries. This is because although a preceding-year product innovation to market (L1.MPD) has affected sales growth of manufacturing firms at the $p < 10\%$ level, that of product innovation to firm has affected sales growth of same firm at $p < 1\%$ level. What is more, whereas previous-year product innovation to firm has brought a 0.76% increase in the sales growth of manufacturing sectors, preceding-year product innovation to market has increased sale of the same sector by 0.03%. However, current innovation introduced to market—like current innovation produced at firm—does contribute greatly to the sales volume of the manufacturing sector, and the presence of current product innovation in market is responsible for increasing sales growth by 0.10%.

The implications on sales growth of the first lag and current product innovation to market in the service sector is not very different from the effect that the first lag and current product innovations to firm have had on sales in the service sector. It is the preceding-year product innovation introduced to firm and to market that contribute greatly to sales growth of services, whereas current product innovation to firm or to market does not—though positive—result in any extensive impacts on sales growth. It, therefore, appears that in the services sector, previous-year product innovation to firm/market—not current product innovation—has considerable impact on sales growth.

Further, analysis of the first lag of product innovations to market and its current value reveals that these innovations have brought positive in-

fluences on performance of *labor productivity* in both firms. However, unlike the first lag of product innovation to firm, which brought significant impact on productivity in manufacturing industries, the first lag of product innovation to market does not have a strong impact on current labor productivity in the manufacturing sector. This demonstrates the differences in the implications of innovation persistence from the point of view of product innovations to firm and to market. The performance of productivity of labor in the services sector has, nevertheless, been influenced to a large extent by the first lag of product innovation to market, with the level of impact being robust at $p < 5\%$ level. This is similar to the first lag of product innovation to firm, which influenced the productivity of the service sector.

Yet, the elasticity of labor productivity with respect to the first lag product innovation to market and product innovation to firm are different in that, while the introduction of product innovation to market in last year resulted in a 6% growth in labor productivity, that of product innovation to firm in the previous year has spurred productivity of labor by about 5% in the services sectors. This shows that the growth of output per unit of labor in the service sector is more responsive to previous-year innovations introduced to market. One possible explanation for this is that service sectors such as telecommunication, finance, banking, and insurance, due to their nature of global linkage, produce new products more often to market than to firm, thus increasing the performance of productivity better than what product innovation to firm can do in service sectors.

Notwithstanding the insignificant implication of the first lag of product innovation to market on productivity in manufacturing sectors, the effect is robust at $p < 0.01$ when current product innovation to market is used. This may indicate that innovation to market has an immediate and strong effect on productivity, then tends to have no meaningful effect. In service firms, however, product innovation to firm in its first lag and current form has positive and significant effects on labor productivity.

A third firm performance predictor is that of *process innovation*, also called *cost reduction innovation*. As previous studies have shown, this innovation is believed to play a crucial role in firm performance. The estimation reveals that the first lag (L1.REK) and current (REK) process innovation have strong positive effects on the demand and supply of labor (employment) in manufacturing but only positive influence in the ser-

vices sector. In the manufacturing sector, the introduction of new processes, methods, and approaches, with a view to increasing efficiency and reducing associated costs, greatly contributes to employment growth at $p < 1\%$. Process innovation introduces new, significantly improved and techniques in order to decrease costs associated with the production and distribution of goods and services and, in doing so, increases efficiency as well as firm performance. I have observed this to be the case in manufacturing sectors, though the case for services is positive yet not robust.

In both sectors, the conditions under which employment has been influenced by current process innovation is not only helpful but also strong, where the level of the impact is robust at $p < 0.01$ in the manufacturing and services sectors. This result, compared to how the first lag of process innovation affected employment, may imply that the effects of process innovation are more effective in increasing the opportunity of employment growth when the newly introduced process innovation is enacted in the same year in which it is created instead of in the following year. This being the case, the result also indicates that persistent effects of process innovation in this particular study are not strong enough to have major uniform effects on employment growth in manufacturing and services firms.

Cost reduction also has positive effects on sales growth. More specifically, in both sectors the first lag (L1.REK) and current (REK) cost reduction innovation have positive impact on sales growth, and the feedback is particularly strong in the manufacturing sector. In the services sector, the strong implication of cost reduction innovation on sales growth is felt only when the preceding year's innovation is used, providing evidence that introduction of new methods and techniques increases firm performance through sales growth differently in manufacturing and services sectors.

For the service sector, a time lapse is required to observe how the introduced process innovation would affect sales growth, whereas in the manufacturing sector, the introduction of process innovation and its effect on sales growth is observed in the same year. The case in service sectors shows the importance of persistence of innovation activities. In fact, there could be different explanations for why innovation tends to persist and how persistence can affect sales. First, it might be caused by true state dependence in that a causal behavioral effect exists, in the sense that the decision itself to innovate in one period enhances the

probability of innovating in the subsequent period (Peters, 2008). The theoretical literature delivers several potential explanations for state-dependent behavior, among which the most prominent works relate to (a) the assumption that success breeds success (Mansfield, 1961), (b) the presumption that innovations involve dynamic increasing returns (Malerba and Orsenigo, 1993; 1995), and (c) that of the sunk costs in R&D investments (Schmalensee, 1992; Sutton, 1991). Second, firms may possess certain characteristics that make them particularly "innovation prone"—more likely to innovate. To the extent that these characteristics themselves show persistence over time, they will induce persistence in innovation behavior and eventually helping the firm to increase sales. Persistence of innovation might, however, be affected by firm-specific attributes of observable characteristics, such as firm size, competitive environment, financial resources, and unobservable features.

As Peters (2008) clearly explained, managerial skills and risk attitudes are vital for a firm's decision to innovate but are typically not observed. If unobserved determinants are correlated over time but are not appropriately controlled for in estimation, past innovation may appear to affect future innovation merely because past innovation picks up the effect of the persistent unobservable characteristics. In contrast to true state dependence, this feature is called spurious state dependence. Luckily, the estimated dynamic panel model cancels the unobserved firm specifics and captures the problem of serial correlation of error terms. It is not, however, possible to explain the persistence effects of process innovation on sales growth in service sectors with certainty as only the first lag of process innovation has been used: only deeper lags can have a clear telling effect on whether innovation persistence could have great effects.

Firm performance is not only factored by innovation output (product innovation to firm, product innovation to market, and process innovation). Indeed, other factors, such as whether a firm is involved in *export* activities, has *networks* with other companies, or has *corporate group* in Germany, can affect firm's employment, sales, and labor productivity status. As expected, having business networks with other enterprises or sister companies is observed to increase employment in the manufacturing sector, but the effect is not strong, suggesting that the manufacturing sectors can even increase employment opportunity without having or developing networks with sister companies. It may also indicate that manufacturing firms could stand alone without needing business net-

works to manage employment conditions. This condition can hold true, especially if the economies of scale of the manufacturing firms are strong enough and, as such, can be independent enough to manage their employment without having had any interaction with other firms. In services; however, membership with other companies has not only positive but also strong contributions to growth of employment. This may imply that service industries (banking, insurance, finance, and telecommunications) that have networks with similar business enterprises within Germany tend to increase the opportunity of the employment. Moreover, being part of a corporate group has helped to boost sales in both sectors. Evidence shows that a firm that develops networks or cooperates with other business companies or enterprises tends to greatly improve its sales performance. Consistent with economic theory, being part of corporate group has greatly helped firms to grow their sales, regardless of firm size and level of technology used. I have also found that a firm that is part of a corporate group within Germany has positive and robust influence on productivity of both sectors at $p < 1\%$. Yet it is in the manufacturing that the elasticity is found to have more impact; having membership induces productivity to grow by 0.08% in manufacturing and 0.06% in services.

The variable export has strong effects on employment in both sectors with the extent of the effects being strong at $p < 0.1$. However, a comparison of the effects in both sectors reveals that the elasticity of employment growth with respect to exports is more in the manufacturing sector than in the service sector (it is 0.038 for the manufacturing sector and 0.019 for the service sector). Further, it is disclosed that being an exporter of goods and services greatly increases the performance of sales growth in manufacturing and service industries. The elasticity of sales growth with respect to export in both sectors is not only positive but also substantial, and engagement in export activities spurs sales growth by about 10% in both firms—a striking coincidence that the response of sales growth in both sectors is the same in magnitude and sign. Similarly, firms engaged in export activities spur productivity positively, with the growth effect being substantial at $p < 10\%$ in manufacturing sector and at $p < 5\%$ in service sectors. This implies that exporting induces more growth effects in services than in manufacturing firms.

Table 2.14

Two-step SGMM estimates for innovation output-driven firm performance

Explan-atory varia-bles	Employment growth		Sales growth		Labor productivity growth	
	Manufac-turing	Services	Manufac-turing	Services	Manufac-turing	Services
	ρ (sta. err)	ρ (sta. err)	ρ (sta. err)	ρ (sta. err)	ρ (sta. err)	ρ (sta. err)
L1.EMP/	.833 (.015)***	.803 (.015)***				
L1.SAL			.768 (.033)***	.783 (.031)***		
L1.PROD					.494 (.025)***	.726 (.025)***
L1.FPD	.005 (.007)	.016 (.012)	.062 (.019)***	.046 (.031)	.031 (.014)**	.057 (.025)**
FPD	.012 (.007)*	.044 (.014)***	.078 (.027)***	.068 (.042)*	.042 (.019)**	.029 (.035)
L1.MPD	.006 (.007)	-045 (.011)***	.038 (.022)*	.012 (.032)	.017 (.017)	.065 (.026)**
MPD	.019 (.007)***	-.012 (.012)	.102 (.034)***	.083 (.042)**	.089 (.024)***	.115 (.030)***
L1.REK	.028 (.007)***	.020 (.011)	.024 (.017)	.065 (.017)***	.016 (.015)	.110 (.021)***
REK	.027 (.008)***	.051(.012) ***	.041 (.020)**	.024 (.021)	.031 (.022)	.003 (.031)
EXP	.038 (.020)*	.019 (.010)*	.101 (.036)***	.105(.039) ***	.039 (.021)*	.049 (.019)**
MEM	.015 (.016)	.073 (.020)***	.365 (.057)***	.092 (.036)**	.083(.026) ***	.069 (.017)***
Year dummy	included	included	included	included	included	included
AR (1)	z = -4.69 Pr > z = 0.000	z = -3.38 Pr > z = 0.001	z = -2.27 Pr > z = 0.023	z = -4.29 Pr > z = 0.000	z = -2.60 Pr > z = 0.009	z = -5.14 Pr > z = 0.000
AR (2)	z = 0.28 Pr > z = 0.779	z = 1.67 Pr > z = 0.094	z = 1.44 Pr > z = 0.150	z = 1.61 Pr > z = 0.108	z = 1.46 Pr > z = 0.146	z = 0.96 Pr > z = 0.339
Hansen overid.	x^2 (191) = 195.14 Pr> x^2= 0.403	x^2 (191) = 199.29 Pr> x^2= 0.326	x^2 (123) = 116.6 Pr>x^2 = 0.645	x^2 (123) = 105.06 Pr > x^2= 0.877	x^2 (189) = 209.26 Pr > x^2= 0.149	x^2(169) = 188.68 Pr>x^2 = 0.143
Obser-vations	4175	2472	4175	2472	4175	2472
Firms	1802	1099	1802	1099	1802	1099

Standard errors in parentheses, $*p < 0.1$, $**p < 0.05$, $***p < 0.01$

To sum up, an important aspect of the discussion of the impacts of innovation output on firm performance (employment, sales, and labor productivity growth) is identifying the appropriateness of the estimated model. That is, a test of serial correlation of error terms and over-identification of instruments is necessary to prove that interpretations of the results are based on a properly-specified model. In the employment growth model, I find that the Arellano-Bond test for first order AR (1) has $p = 0.000$ in the manufacturing and $p = 0.001$ in the services, whereas the second order test AR (2) has $p = 0.779$ in the manufacturing firms and $p = 0.094$ in the services firms. These indicate that the null hypothesis that $Cov(\Delta\varepsilon_{i\,t}, \Delta\varepsilon_{i\,t-k}) = 0 \ for \ k = 1, 2, 3$ is accepted because $p < 0.05\%$ in its first order and $p > 0.05$ in its second order, confirming that error terms are serially uncorrelated. What is more, the Hansen over-identification test, with $p = 0.403$ in the manufacturing and $p = 0.326$ in service firms, both of which are above the threshold of $p > 0.05$, indicates that the number of instrumental variables used are not over-identified, showing an absence of serial correlations between instruments. Therefore, the estimated model is found to be properly identified.

In the sales growth model, a test of the specification in its first order AR (1) has $p = 0.023$, and in its second order, AR (2) has $p = 0.150$ in the manufacturing sector. In the services sector, AR (1) has $p = 0.000$ whereas AR (2) has $p = 0.108$. The test shows that in both sectors, AR (1) $p < 0.05$ whereas AR (2) $p > 0.05$ shows that there is no serial correlation of the idiosyncratic terms. Furthermore, the estimation shows that the number of instruments used is not over-identified. This is because the Hansen test of over-identification, with $p = 0.645$ in the manufacturing sector and $p = 0.877$ in the services sector, shows that instrumental variables used are not over-identified and that the instruments are valid, because in both sectors $p > 0.05$.

Moreover, the innovation output-induced labor productivity model of manufacturing and services shows that all the discussions made are based on properly specified models. This is because the tests demonstrate no serial correlations and no problem of instrument over-identification. The serial correlation test shows that in manufacturing firms, AR (1) has $p = 0.000$, AR (2) has $p = 0.146$, and Hansen test has $p = 0.149$—all within required levels. In the services sector, AR (1) has $p = 0.000$, AR (2) has $p = 0.339$, and the Hansen test has $p = 0.143$. All p-values in the first order of both sectors are less than 0.05, and those in the second or-

der are greater than 0.05, indicating that labor productivity growth models in the manufacturing and services sectors accept the null hypothesis that error terms are serially uncorrelated. The acceptance of the null hypothesis proves that idiosyncratic error terms are not correlated. Moreover, the Hansen test, which is well above 0.05 in both industries, shows that instruments used are not over-identified and, in fact, are valid.

2.7   Conclusion

Increasingly, the competitiveness of firms depends on the capability to innovate, to learn, and to coordinate with other sectors. A vast number of studies—especially following the *Frascati Manual* and *Oslo Manual* of innovation—have confirmed that innovation has a multiplier effect on the performance of firms. Indeed, a large volume of literature reviewed in this essay shows that innovation can have positive or negative implications on the employment, sales, or labor productivity of firms, depending on the kind of innovation or technology used as well as on the method of estimation. Moreover, the essay has shown that most empirical evidence have estimated the innovation-firm performance relationships using either innovation input or innovation output in manufacturing sectors without making a comparative study between input and output indicators in manufacturing and service firms; use either short panel data or cross-sectional data without taking true state dependence which can have important implications on performance of firms. In an attempt to address these gaps, I have estimated the effects of innovation input and innovation output on employment, sales, and labor productivity growth in manufacturing and service sectors in Germany based on survey panel data that covers the years 2003–2010. The estimation result has been reported in two parts: in the first part, the effects of innovation input on employment, sales, and labor productivity are interpreted, and the second part discusses the effects of innovation outputs.

I identify three variables as indicators of innovation input: R&D intensity, investment innovation intensity, and total innovation intensity. In addition, I include export and corporate membership as control variables. The result shows that the first lags of R&D intensity, investment innovation intensity, and total innovation intensity have crucial effects on employment growth in both sectors, with the extent of impacts and elasticity of employment growth varying between the manufacturing and services sectors. Against their lags, current R&D intensity and present

investment innovation intensity have, however, had negative effects on employment in both the manufacturing and service sectors. What is more, being an exporter and a member of a corporate group has consistently been found to have strong positive effects on employment in both sectors. One important difference among the employment growth effects of innovation inputs is that it is in the services as opposed to the manufacturing firms that the effects are observed to be more robust; that is, growth in employment is more responsive in services than in manufacturing firms.

Except for current total innovation intensity, all other variables, including R&D intensity and its first lag, investment innovation intensity together with its first lag, export, and being a member of corporate group, have increased sales growth of manufacturing and services. The negative role of total innovation intensity may indicate that allocation of resources for total innovation (aggregates of R&D expenditure, investment innovation, and recurrent innovation), including for hiring R&D experts, providing training services for research associates, buying research facilities, preparing conference venues, and the like, can shrink sales volume as these activities would shift resources, eventually leading to negative consequences. Moreover, I find that elasticity of sales growth is much more responsive in manufacturing than in service industries.

With respect to the performance of labor productivity, I have obtained that though the amount of resources allocated for R&D as well as for investment innovation is found to have increased the productivity of labor in both sectors, the share of expenditure on total innovation appears to be negative in manufacturing and service firms. I find this to be similar to what has happened to the impacts of total innovation intensity, which has negative effects on sales growth. Overall, the growth of labor productivity seems to be more responsive to innovation inputs in service firms than in manufacturing firms.

In the second part of the essay, I have interpreted the results of the influence of innovation output on employment, sales, and labor productivity. In doing so, I measure innovation output by three variables: product innovation to firm, product innovation to market, and process innovation. The finding reveals that whereas current product innovations to firm (introduction of new or significantly improved goods and services) have significant effects on employment growth, the influence with which the first lag of product innovation to firm has on employment growth is

not robust in both manufacturing and service firms, suggesting the possibility that a firm needs to buy time to realize the effect. Product innovation to market in its first lag and current values, contrary to product innovation to firm, has negative impacts on employment growth in service firms. In the manufacturing sector, the effect is positive and even significant when current product innovation to market is used. This shows that there is a difference between manufacturing and service firms in response to the introduction of goods and services in the market. Further, I find that cost reduction innovation has crucial roles in boosting employment growth in both sectors. A useful distinction to be observed is that although most innovation input and innovation output indicators have positive and robust impacts on growth of employment in both sectors, it appears that *innovation input seems to be superior to innovation output* in explaining employment growth. It is also noteworthy that the elasticity of employment growth with respect to innovation indicators differs between manufacturing and service firms.

For the sales growth model, all innovation outputs (product innovation to firm, product innovation to market, and process innovations, including the corresponding lags), have positive effects on sales growth. However, two things are worth noting: (a) innovation output are less powerful to innovation input in explaining sales growth, and (b) innovation output is more responsive in manufacturing sectors than in service firms. Moreover, all innovation output indicators (product innovation to firm, product innovation to market, and process innovation, including their lags) have positive (some with robust and some without) influences on labor productivity growth—much of the effect felt in service sectors. Two things need to be noted. First, innovation output, compared to innovation input, generally has less influence on productivity of labor (innovation measured quantitatively through innovation input influences labor productivity growth more than what the qualitative innovation output can affect productivity). Innovation inputs are objective measures based on money allocated for innovation activities while innovation output indicators are subjective measured by binary responses of "yes, innovation is introduced" or "no, innovation is not introduced." The fact that productivity of labor is explained better by innovation inputs than innovation outputs demonstrates that objective measures of innovation is, overall, better than subjective measures of innovation in driving productivity. Second, the extent of the impact innovation output has on

labor productivity differs between manufacturing and services sectors—
the service sector is more responsive than the manufacturing sector.

Notes

[1] Entrepreneurs generate new ideas, production systems and processes that keep
the economy grow. They are endowed with (innate or learned) ability in provid-
ing new ways and are engaged in creative destruction that produces innovation
and technological change. An important aspect here is that of entrepreneurship-
also called a risk taking action-the capacity and willingness to develop, organize
and manage a business venture along with any of its risks in order to make a prof-
it. Entrepreneurship combined with land, labor, natural resources and capital can
produce profit and that entrepreneurial spirit is characterized by innovation and
risk-taking, and is an essential part of a nation's ability to succeed an ever chang-
ing and increasingly competitive global marketplace. Entrepreneurship-most
commonly associated with the creation of new business, establishment of new
firms as well as start-ups-is strongly linked to innovation. More information
about the role of entrepreneurship in innovation or the relationships between
entrepreneurship and innovation can be referred from any relevant literature(D.
B. Audretsch, Keilbach, & Lehmann, 2006; D. B. Audretsch, 1995; D. Audretsch
& Vivarelli, 1996; Baumol, 1990; Parker, 2009). In this essay the implication of
entrepreneurship on innovation is not, however, dealt as the purpose is rather on
understanding the role innovation may have on firm performance.

[2] Innovation increases efficiency and value added of firms where the overall im-
pact creates mechanisms that eventually make the firm competent and resilient
(OECD, 2005)

[3] Conventional innovation literature takes expenditure on R&D and number of
grants issued as main indicators of innovation. This approach measures aspect of
technological innovation and literature of neoclassical innovation takes intangible
capital (knowledge), process innovation, and organizational and marketing inno-
vation.

[4] Product innovation is about the development, production, and release of tech-
nologically new products.

[5] This has to do with process innovation, which is contextualized by adopting a
technologically new or improved production process, equipment, and product
delivery method in order to reduce production cost or to improve productivity or
product quality. For instance, providing a new insurance service can be one ex-
ample of product innovation, and introducing a new software or networking sys-
tem can be process innovation in the insurance industry. In general, product in-
novation tends to be radical, and process innovation tends to be incremental.

[6]Innovation-driven change is intended to improve existing conditions. The level of improvement—depending on the effort made—can be minimal or significant. The intended change may be applied to reform or transform the firm, business, organization, and economy, and so forth in ways that satisfy demands.

[7] While the introduction of new or original products, processes, organizational or market structure change is considered to characterize radical innovation, modification of the existing products, process, organizational and a market condition is assumed to be incremental innovation. The usual problem here is making a clear distinction between the new and modified innovation and identifying indicators for the completely original and the substantially improved components of innovation. More information about radical and incremental information can be refereed from the works of Carroll and Hannan (2004)

[8]An extensive literature on innovation indicators and measurement can be referred from the recently published book "*Handbook of Innovation Indicators and Measurement*" (2013). This book, edited by Fred Gault, has seven parts: why innovation matter, defining innovation and implementing the definitions, measurement, developing and using indicators, innovation strategy, beyond the horizon and the challenges all of which are contributed by best scholars of innovation (Gault, 2013). Moreover, more information about the definition, measurement, innovation and development, new directions of innovation, and the role of the players in innovation can be referred from a book on "*Innovation strategies for a global economy*"(Gault, 2013)

[9]Albeit the high-tech and medium-tech knowledge-intensive services are being used as indicators of innovation, it is not common to see the less knowledge-intensive services serving as indicators of innovation. This is because firms that have invested less intensive knowledge services are expected to have less or no contribution to new products or process and, hence, innovation. In most small businesses, we find the extent of knowledge being applied less and, therefore, less probability of innovation and competitiveness.

[10] There exists a large number of literature on the study of innovation-firm performance relationships (Aw, Roberts M., & XU D., 2009; Coad & Rao, 2011; Colombelli, Haned, & Le Bas, 2013; B. H. Hall, Lotti, & Mairesse, 2012; Szczygielski, Grabowski, & Woodward, 2013).

[11] Institute for Economic Research at the University of Munich.

[12]Intensity measures the share of R&D expenditure from total turnover of the firm. An increase in the amount of R&D expenditure, *ceteris paribus*, tends to increase the intensity of R&D and is likely to beef up the likelihood of innovation of the firm. Similarly, a decrease in the R&D expenditure tends to decrease the firm's chances to innovate and to be competitive.

[13]Similar studies on innovation-firm profitability relationships (Geroski et al., 1993).

[14]One can interpret the lagged margins term as reflecting cash flow influences on innovative activity that feed through to innovation and, hence, to profitability within a year or so. Indeed, one might wish to endogenize the variables measuring current innovation rates to ensure that any contemporaneous feedback from profits to innovations does not create bias. However, we believe that cash flow is much more relevant to decisions about the level of research inputs a firm chooses than to the timing of innovative output, and it is certain that feedback between profits and innovative output operate with very long lags, if at all.

[15]This is, however, not true in actual implementation because value added is seldom deflated by firm-specific deflators, implying that the demand-shifting effect of innovation is also included in the variable. Nevertheless, the usual interpretation of the coefficients of the standard model implicitly assumes no market power for the firm on the demand side. For details, see Mairesse and Jaumandreu (2005).

[16] The survey shares the properties CIP data but also has unique features. First, unlike CIS, MIP is an annual panel survey which provides more opportunity to analyze the persistence of innovation activities and causal effects between innovation input and innovation output, and between innovation and firm performance. Second, and more importantly, MIP survey goes beyond the standard CIS questionnaires and includes data on firm performance (profitability and gross value added) and firm's market competition (Peters and Rammer, 2013)

[17] This applies to NACE (rev.1.1) 15.9, 22.1, 24.4, 36.1, 64.3, all groups of 74, 92.1, and 92.2.

[18] MPO denotes medical, precision, and optical instruments.

[19] Industry classification is based on the classification system NACE rev.1.

[20] Note that in Germany, the terms *industry* and *manufacturing* are interchangeably used. This is, however, not the case in the common usage and interpretation of the concept of manufacturing and industry, where the latter usually incorporates the former as opposed to the case that the former can't include the latter.

[21]Community Innovation Surveys (CIS) based firm-level innovation studies consider firms that employ at least 10. However, in Germany the minimum standard firm size for innovation research is set at five, and all firms are classified into eight groups: (a) 5–9, (b) 10–19, (c) 20–49, (d) 50–99, (e) 100–199, (f) 200–499, (g) 500–999, and (h) firms that employee at least 1,000. Firms that employ up to 49 are considered to be small which means that the first three groups all fall within the small business category. We find an industry that employs as many as 6,000, which is exceptional. Moreover, we find that industries that employ more

than 1,000 make up less than 3% of the total net sample. Because these industries have extreme values and are likely to seriously affect estimation results, we delete all firms (manufacturing and services) that employ more than 1,000.

[22] Details on recurrent innovation intensity are explained in the estimation results (part eight) of the paper.

[23]If deeper lag lengths of dependent variable were included (such as second lag or third lag), then the total number of observations could have been significantly reduced, and, thus all estimations could possibly have non-robust results. This is the case, as the data is unbalanced panel.

[24] All estimations are made on the basis of xtabond2 syntax. More information about the techniques of using dynamic panel models can be obtained from Roodman (2009).

[25]Innovation is about novelty and is the generation, production, or creation of new or significantly improved goods and services. It is also a method, technique, or approach designed to increase efficiency as well as reduce costs in the production and distribution of costs. Such activities do not necessarily come overnight; the process should take sufficient time between participating in innovation activities and realizing their impact on firm performance. Due to this feature, lags of innovation input more than current innovation input has a better impact on employment growth.

[26] He, however, underscored that such big picture is a summary of the results obtained from studies in a qualitative way. He continues in arguing that such attempts to extract information on the size of the effects—the economic relevance, not the statistical significance—is hindered by the absence of a reasonably high degree of comparability across the studies. The lack of comparability, among others, is attributed to differences in the unit of analysis (establishment vs. enterprise), the sampling frame (all firms versus firm with a number of employees above a certain threshold only), the specification of the empirical models estimated and the econometric methods applied. His study suggested that the establishment of standardized approach in the analysis of the implication of international trade (export and import) on firm performance is needed and, further, acknowledged the adoption of the International Study Group on Exports and Productivity (International Study Group on Exports and Productivity (ISGEP), 2008).

[27] The Oslo manual of innovation, which is used as a guiding principle in collecting and interpreting innovation data, takes innovation output as product innovations, regardless of the kinds of goods and services produced. Because this essay is based on data generated from MIP, which is based on CIS (a direct construct of the Oslo manual), we treat innovation output as product innovation (new products to a firm, new product to a market, or new process innovation) throughout the study.

Essay III

How big is the impact of technological innovation on regional economic performance?
Evidence from Germany

3.1   Introduction

Technological innovation plays a central role in economic growth. A change in technology provides incentive for continued capital accumulation and, in turn, accounts for much of the increase in output. The positive relationship between technological innovation[1](TI) and economic growth has long been identified in formal growth models (Kydland and Prescott, 1982; Romer, 1990; Solow, 1956, 1957). The neoclassical growth model of Solow (1956, 1957) recognizes technical change[2] as an exogenous variable that plays a critical role in long-run economic growth. Arrow (1962) acknowledges that a constant growth of technology, apart from the quality of labor force, has a crucial impact on long-term economic growth. Other scholars, including Uzawa (1965), Phelps (1966), Conlisk (1967; 1969), and Shell (1967), provide enormous insights on the wider role of technological innovation in economic growth, competitiveness, employment, and productivity of nations. The recent past models of endogenous growth by Romer (1990), Grossman and Helpman (1991), Grossman (1993), and Aghion and Howitt (1992) have shown that allocating resources for generation of new technologies or innovation leads to a continuous rise in the economic growth of nations. It then goes without saying that the production and application of technology in regions will not only bring about different level of economic and noneconomic advancements but will also have considerable effects on future income differences and development[3] of the regions.

Although the positive economic growth or economic development implications of technological innovation has already been well received,

124

there are no clear empirical evidences of whether the theoretical associations between technology and growth are direct or indirect, automatic or gradual, temporal or sustainable, and linear or nonlinear. By the same token, there is no clear evidence on whether new discoveries,[4] R&D activities, and the presence of researchers have direct or indirect effects on technological innovation and, in turn, on economic development. In fact, some scholars such as Jones (1995; 1995) have been at odds with the view that researchers are able to generate technology that will ultimately increase the opportunity of economic growth. This observation is made on the basis of the substantial rise in the number of researchers over the last 40 years, but only less proportionate economic growth has been observed.

The view that technological innovation contributes to regional economic growth and development is no longer an issue, but the extent to which technological innovation impacts the economic performance of regions has not been systematically analyzed. The purpose of this essay is, therefore, to address this issue by analyzing the effects of technological innovation on the economic performance of the planning regions in Germany (Appendix C1). To this end, the paper attempts to answer four questions: How significant is technological innovation in explaining regional per capita income growth? To what extent does technological innovation affect regional employment growth? How big is the regional wage growth effects of technological innovation? And how important is the impact of the true state dependence on economic performance?

A planning region in Germany, in terms of size, refers to a region in between NUTS2 and NUTS3 consisting of at least one core city and the surrounding area. The advantage of taking planning regions instead of NUTS3 (districts) as spatial units of analysis is that they can be regarded as *functional units* in the sense of travel-to-work areas and because they account for economic interactions between districts. A district (NUTS3), on the other hand, may be a single core city or a part of the surrounding suburban area, whereas NUTS2 has aggregated data and is not able to provide detail information about the economic dynamics of cities and surrounding areas. Planning regions are slightly larger than labor market regions (Fritsch and Schindele, 2011).

The motivation to undertake the present study at planning regions in Germany is based on two reasons. First, Germany has been one of the leading countries in the world in technological innovation, and it is a

country that has a strong economic policy at regional level. Nevertheless, the impact of technology on economic growth has not been studied well at the planning region level. Second, data on R&D expenditure, which is one of the indicators of technological innovation, has been archived well at planning regions of Germany; nevertheless, the extent to which R&D intensity affects economic performance of planning regions have not been assessed, at least not scientifically or comprehensively.

The object of the study is economic performance, which is expressed by growth of per capita income (PCI), employment, and wage; the driver of the object, that is, technological innovation, is measured by R&D[5] expenditure, share of researchers, and number of patent rights applied for per 100,000 people or population. The study is based on panel data of five years—every two years between 2001 and 2009—where data are accessed from the IAB, Stifterverband, and Federal Statistical Office of Germany (details in the data section part of the essay). In addition to the panel data, I take the five years' average cross-section to estimate the implications of TI on economic performance. I do a cross-section and panel data analysis in order to provide a better understanding on whether growth literature is better captured by cross section or panel data. Of course, cross-sectional and panel data and their respective models have limitations and advantages [6]in estimating growth equations.

The paper has seven parts, including the foregoing introduction. In the second part, I provide a review of literature on indicators and measurements of technological innovation along with a review of the previous empirical contributions on the implications of innovation on economic performance at different levels of analysis. This is followed by explanations of how the current research differs from previous contributions and, in doing so, how the present paper contributes to knowledge. In part four I present an empirical econometric model and the estimation strategy employed to answer the research questions. Descriptions of data and summary statistics are presented in part five while discussion of estimation results are provided in part six. Finally, I provide conclusion.

3.2   Technological innovation: Indicators, measurements and empirics

In Essay II, concepts, indicators, and measurement of innovation have been reviewed. The focus has been at firm level, and the indicators ex-

plained have also been customized to firm-level analysis. In this part of Essay III- different from essay II-I introduce some other indicators employed to describe and measure TI, which helps to set up a framework for the analysis. This is followed by a review of some previous empirical studies on the relationship between technological innovation and economic performance with the purpose of understanding the ways in which previous studies might be related to or different from this essay, thereby, in identifying how the present contribution adds values.

3.2.1 Technological innovation: Indicators and measurement

A fundamental driver of economic development, technological innovation is defined as a production or introduction of new or significantly improved goods or services aimed at improving productivity as well as efficiency. It involves elements of invention, innovation, and diffusion. In an attempt to provide standardized measurement for TI through different indicators, a number of efforts have been made where the Solow model, one of the most influential models developed in the 1950s, for example, considers technology as a residual component which can be quantified through capacity utilization (Basu, 1996) and labor hoarding (Burnside, Eichenbaun, and Rebelo, 1995; Weil, 2009). Indeed, the residual model is a neoclassical growth model that attempts to explain long-term economic growth or development by looking at productivity, capital accumulation, population growth, and technological progress. The insight is that technological progress is taken as residual and therefore exogenous, which has to be obtained from outside. According to Solow, the residual, which has to be generated or accessed from outside, is considered critical for economic development, although in the new growth theory, treating technology as exogenous receives considerable criticism and debates.

Some argue that direct measurement of technological innovation or technology involves quantifying the share of potential users that have adopted a given technology at a point in time (Gort and Klepper, 1982; Griliches, 1957; Mansfield, 1961; Skinner and Staiger, 2005). This approach has, however, two drawbacks. First, although it captures the extensive margin of technology adoption, such measurement neglects the intensive margin (how intensively each adopter uses technology). Second, its computation requires use of hard-to-obtain micro level data. Consequently, diffusion of a limited number of technologies for a few

countries or subjects of analysis can be documented using such measures.

The European Commission has developed four main indicators in measuring technological innovation or technological change: the share of R&D[7] expenditure, extent of high-tech and knowledge intensity being used, the number of patent rights applied for or granted per 100,000 people, and share of R&D (also called the scientific human resource component) employees with tertiary education. Among others, the most commonly used high-tech product indicators include aerospace, computers (office machines, electronics), telecommunications, biotechnology, pharmacy, scientific instruments, electrical machinery, chemistry, nonelectrical machinery, and armaments. Although these indicators represent the hardware components of technology, the intensive knowledge being used in producing high-tech typify software components of technological innovation.

Technological innovation is also identified by extent of basic and experimental R&D[8] being used. Two important contributions in this context are the *Frascati Manual*, which covers the measurement of the whole scientific and technological activities at national level(OECD, 2002), and the *Regional Manual*, focusing on R&D statistics and innovation methodologies at the regional level (Eurostat, 1996). Both manuals clarified the concepts on two fundamental categories of research activities—the basic and experimental R&D, which comprises innovative, works undertaken on a systematic basis in order to increase the stock of knowledge, and the use of this stock of knowledge to devise new applications. In this context, R&D covers three categories: basic research, applied research, and experimental development.

Basic research indicators include R&D expenditure and R&D personnel. Both of them—in Europe and in most OECD countries—are available at national and regional level. At the national level, there are intramural expenditures and R&D personnel. Moreover, all persons employed directly in R&D are counted along with those providing direct services for research: R&D managers, administrators, and clerical staff at national and regional levels. However, the inclusion of research support providers, instead of only researchers, could bias taking R&D as an indicator of TI. Czarnitzki and Thorwarth (2012) take basic research as a very early stage research designed to build a knowledge base in order to understand fundamental principles. It is driven by a scientist's curiosity

or interest in a scientific question. Basic research, unlike applied research and experimental development, which are more commercially orientated, is phenomena oriented and as such barely helps practitioners with their everyday concerns. Nevertheless, it stimulates new ways of thinking, which may lead to the generation of revolutionary ideas, concepts, and applications. An example is modern computer technology, which could not have existed without pure mathematical research—which, at that point in time, was undertaken without any motivation for practical applications in computer science.

The number of patent rights is the other indicator employed to measure technological innovation. The basic guideline for constructing patent statistics as a measure of scientific and technological activities is given in the *Patent Statistics Manual* (OECD, 2009) and in the *Compendium of Patent Statistics* (OECD, 2008). Eurostat's patent database contains three collections of statistical data: patent applications to the European Patent Office (EPO), patents granted by United States Patent and Trademark Office (USPTO), and triadic patent families by earliest priority year. Use of patent data for documenting TI, like the way innovation is measured, has been a conventional approach since long. Also the number of human resources employed in science and technology sectors measure technological innovation, though this is a very crude indicator. Indeed, the number of human resources in science and technology (HRST) can improve understanding of the supply and demand of science and technology personnel—an important facet of the new economy. This domain focuses on two main aspects: stocks and flows. The former shows the needs of the labor force, and the latter indicates to what extent this demand is fulfilled in the future. Within this assemblage, particular attention should be paid to the subset of scientists and engineers—quite often innovators at the nucleus of technology-led development (OECD, 2013).

Human resource in science and technology is defined according to the *Canberra Manual* (OECD, 1995) as a person fulfilling at least one of the following conditions: (a) successfully completed education at tertiary level in S&T field of study or (b) not formally qualified but employed in S&T occupation where the above qualifications are normally required. The conditions of the above educational or occupational requirements are considered according to internationally harmonized standards: International Standard Classification of Education (ISCED) and the International Standard Classification of Occupation (ISCO). Although the uses

of these classifications provide generally data, the systems are not perfect, necessitating the need to improve indicators and measurement of technological innovation. Further, continuous productions of indicators are expected to improve sustainable TI or innovation and, in turn, sustainable economic development. Table 3.1 presents indicators of technological innovation used in the current study. In the following section, I review empirical findings on technological innovation and its impact on economic performance, which then leads to estimation strategies.

Table 3.1
Indicators and measurement of technological innovation

Variable	Indicators	Measurement description
Technological Innovation	Share of researchers	Share of R&D employees (research scientists) with university-level qualifications from total working labor force
	R&D expenditure	Expenditure on public and business R&D
	Patents applied or granted	Number of patents applied or given in areas of high-tech, ICT, and biotechnology
	Extent of technology	High-technology, medium-high-low-technology
	Knowledge intensive activities	High-tech and medium-tech knowledge-intensive services as well as market knowledge-intensive services

Source: Author's construction based on OECD and EPO of different years.

3.2.2 Empirical contributions

Research on the implications of technological innovation, like any other study, covers a wide range of areas. One strand of literature deals with how a change in technology responds to employment. Some attempt to examine the relationship between technological change and productivity, and others focus on the dynamics between technology and competitiveness. Clearly, various studies use different methods and models, depending on the purpose of the study and data availability at different levels of analysis, including at national, regional, industry, and firm levels. In this subsection, I review previous empirical studies that are thought to have

some input to the present study. Literature on firm-level impact of technological innovation is not included as it was covered in Essay II.

Scholars who have analyzed the implications of TI on economic growth at *country level* identified that technology is, indeed, an integral part of competitiveness. For example, the contributions of Roessner, Porter, Newman, and Jin (2002) reveal that TI constitutes the most dynamic and decisive factor in the new productive forces, has become an important means of rising labor productivity, and constitutes a substantial cornerstone for the edifice of modern economy. Moreover, their study indicates that the development of innovative technologies and advancement of manufacturing capabilities positively stimulate economic growth and that TI is central for national competitiveness. Besides, a strong correlation between national and technological competitiveness and mutual causal effects has been confirmed by the works of Antonelli and Liso (1997), Archibugi and Michie (1998), Clark and Guy (1998), and Grupp (1995). Moreover, Falk (2007) has shown that spending in high-tech industries contributes immensely to economic growth.

Other scholars have used comprehensive approaches to discern the implications of TI on national economic growth. The work of Castellacci (2002) is particularly important. He used a combination of cumulative causation and technology gap approach to investigate the performance of technology development and productivity growth in 26 OECD countries between 1991 and 1999. The cross-country analysis revealed a range of outcomes: follower countries fell behind leaders; some were partly or totally able to catch up and even to overtake leaders. He noted that even if some follower countries were able to close the technology gap between themselves and the leaders, they may not be able to close the growth rate differential. The result underscores that cumulative causation, which is a component of many economic and noneconomic factors, is set to have a considerable impact on technological differences between surveyed countries where innovation difference would eventually dictate the economic scenario[9] of respective countries.

A similar contribution on TI comes from Wade (2005), whose analysis focused on demonstrating the significance of technological innovation in creating continuous disparities in economic development between developed and developing countries—a reminiscent of the *core-periphery* debate of cumulative causation (Hirschman, 1957; Myrdal, 1957). Wade discussed how elements of globalization have the potential to bring

about the *failure* of nation-states. These elements include north-south terms of trade, including strategies of the more economically dominant countries and global economic multilateral organizations, the industry location decisions of multinational corporations, and the non-diffusion of modern technology to developing countries. These phenomena are likely to have immense effects on the technological conditions of nation states and, simultaneously, on their economic development.

At the *regional level*, a contribution more related to the present essay comes from Bamberry (2006), who estimated the economic development impacts of technological change in the region of Riverina, Australia. He obtained that technological changes have contributed positively to the economic development of a region, and he attributed the positive impact to the region's significant locational character. The growth of the region is particularly noticeable in the wine industry of the Griffith area and in the food processing industry around Leeton, where incremental change, problem solving, and collaboration grew out of interaction between clients and firms at the local level. His findings show the positive impacts of TI and reflect the links in cumulative causation theory between technical progress and location, which is supported by works of Scott and Storper (1992) that "technical innovations are often place bound." They argued that one of the reasons for this is that TI depends on human knowledge and capital and which tend to concentrate in pools of specialized labor that are closely tied to location. Capello and Lenzi, (2013) who analyzed the relationship between innovation and employment growth at regional level (NUTS2) for twenty-seven European countries found that the direct effects of product and process innovation are moderated by specific regional structural characteristics, namely the region's functional specialization and settlement structure. Most importantly, the effect of product innovation on regional employment is positive in regions with a larger presence of production functions, whereas the impact of process innovation is negative in metropolitan settings.

A stylized approach in the study of technological innovation is to measure it by share of R&D expenditure and to investigate how R&D intensity affects economic performance. Falk (2007) measured technological innovation by R&D expenditure in business enterprises, investment expenditure, and average years of education, and estimated the impacts the three variables have on PCI. He obtained that the first lag of

PCI has positive and robust effects on current PCI with the level of elasticity being 0.89—a 1% increase in the amount of PCI of the previous year is followed by a 0.89% growth of PCI, indicating almost one-to-one growth elasticity. With respect to the impact of R&D expenditure on PCI of business enterprises, he found it to be both positive and robust. More specifically, he identified that elasticity of PCI with respect to R&D expenditures is 0.024 in the short run and 0.22 in the long run. Overall, his study is one of the few empirical contributions on the implications of technological innovation on PCI that uses longitudinal data and dynamic panel, a model that takes into account endogeneity, region-specific effects, and time dynamics.

Interestingly, Maddison (1982) tried to compare the difference in total outputs of a nation by taking the technology data of very different periods. More specifically, he estimated the contribution of technological change on gross output or GDP and revealed that output per hour in the Unites States in the 1980s was about 10 times more than output per hour 100 years before (1780s). The difference in output is accounted for by technology, indicating that technology is not only helpful but an absolute requirement for a nation to grow and to keep growth sustainable. Well before Maddison (1982), Abramovitz (1956), and (Solow, 1957b) identified the positive output growth effect of technological change as the human capital component through engagement in R&D activities; and, in turn, improving economic growth was acknowledged by Jorgenson and Fraumeni (1989). Human capital is considered to be the knowledge and skills of individuals to be used to produce technology needed by society. Knowledge and skills obtained from a university education or from experience are used for research and generation of useful products to increase the productivity and efficiency of the economy. Indeed, there is a strong consensus that knowledge competitiveness increases technology competence and, in turn, boosts economic performance.

At *industry level* many studies have analyzed the implications of technological change on industry performance. Salter (1969) reported a positive association between total factor productivity (TPF) growth and employment growth, where TPF is considered to be a result of technological change. Wragg and Robertson (1978) and Ball and Skeoch (1981) revealed that in the United Kingdom, the relationship between the Solow residual and industry employment appears to begin to weaken around 1945, all but disappearing in the 1970s. More ambitiously, Nickell and

Komg (1989) who estimated a three-equation structural system (production, pricing and demand) across nine manufacturing industries between 1974 and 1985, found that labor augmenting technical change is found to depress employment in only two industries—bricks and glass. In none of these studies was technical change explicitly observed; it was always taken as a trended residual. They underscored that effects attributed to TI may really merely reflect omitted variables such as quality of labor, monopoly power, or changes in effort.

To sum up, a review of the empirical literature on the impacts or implications of technological innovation on economic performance at national, regional, and industry levels shows that technology has encouraging effects on the economy, in most cases. Most of the reviewed literature further demonstrates that there exists a strong positive relationship between technological innovation and jobs creation[10]. These studies, however, are not based on panel data and dynamic panel estimation, which takes into account endogeneity problems (includes regional specific effects), omitted variables, and measurement errors. The present study intends to address these gaps. In the following part, I explain how the current study differs from the previous studies and how such contribution would add knowledge to existing literature.

3.3   Contribution of the study

Of the plethora of economic development drivers, technological innovation has been acknowledged for decades. Yet, identifying indicators of technological innovation on the one hand, and knowing which indicators explain economic development better on the other, remains a difficult task. It is true that technological innovation is a product of research, at the core of which are researchers who appear to strongly shape the extent of TI or innovation. However, more often than not, it is difficult to get data on the number of scientific researchers; consequently, measuring innovation by researchers has become tricky and, in turn, the implications on economic performance. This problem is more pronounced at the *meso* (regional) level. In Germany, however, one finds not only rich data on the number of scientific researchers as well as R&D expenditure in planning regions but also the available data are panel. Given this opportunity, this study intends to contribute to existing limited empirical knowledge of the impacts of technological innovation on planning regions' economic performance in Germany in the ways outlined below.

First, previous studies on technological innovation-economic development relationships seem to focus on the firm, industry, or country levels, partly due to the unavailability of longitudinal data at subnational jurisdictions or regions and partly because of the lack of attention given to regional economies. However, currently, due to globalization and information communication technology, regional economies have not only increasingly become necessary for local economies but also have become engines of national and global economies. Given such realities, this study tries to reflect this trend and analyze the extent to which technological innovation might affect the economy of planning regions in Germany. I believe that by taking case studies in Germany, similar research can be conducted in the future and examine how important TI might be in explaining regional economies. The present contribution is not only original in its approach but also detailed in its analysis as it takes three indicators for economic performance (PCI growth, employment growth, and wage growth), which most researches have never dare to work at.

Second, a number of available technological innovation impact studies measure TI using R&D expenditure and number of patent rights. However, the two variables, as indicators of technology, cannot comprehensively capture the intellectual or knowledge aspects of the labor force working in scientific research and who are believed to be the kernels of innovation and regional economy. This study—apart from using R&D intensity and patent rights as indicator of TI—includes the share of researchers as proxy of innovation and, in turn, estimates the effects they have on regional economy. This provides an opportunity to look into the effects of researchers on regional economy as well as to examine whether the share of researchers compared to R&D expenditure or patent rights can better explain regional economy.

Third, most technological innovation impact studies use either cross-sectional or panel data to examine the relationships between TI and economic development. Cross-sectional and panel data both have their own merits and demerits. Cross-sectional data is easy to estimate; however, two main shortcomings surface in using such data in growth estimations. The first shortcoming lies in its treatment of time-invariant specific effects. Standard cross-sectional estimator (whether ordinary least squares or any variant that allows for non-spherical disturbances) is consistent only as long as the individual effect can be assumed to be uncorrelated with the other right-side variables. However, it is easy to see that such an assumption is

necessarily violated in the dynamic framework of a growth regression (Caselli, Esquivel, and Lefort, 1996).

The second criticism has to do with the issue of endogeneity. In most specifications of the model, at least a subset of the explanatory variables might correlate with errors of the vector and, in turn, with the dependent variable, economic growth, or performance. For example, it is reasonable to suppose that the rate of R&D expenditure—a variable included in the great majority of the studies—is determined simultaneously with the rate of economic growth. Although the case is perhaps strongest for narrowly defined economic variables, like the rate of investment R&D, it is reasonable to believe it applies across the board.

The use of panel data, on the other hand, tackles the problems of endogeneity, omitted variables, and measurement errors and thus provides consistent estimations. The panel model captures both cross-sectional and time series data and is expected to provide comprehensive policy inputs on the relationship between technological innovation and regional economic growth. However, its estimation technique, especially the introduction of instrumental variables, complicates interpretations of the results. This is particularly true in the case of two-step SGMM, which this study has employed. The present study, which uses five years' average cross-sectional as well as panel data, intends to address the problem of using either cross-sectional or panel data in economic growth. In the following section, I provide the empirical econometric model and estimation strategy employed to answer the research questions raised in the introductory part of this essay.

3.4   Model specification and estimation strategy

As mentioned before, the purpose of this essay is to estimate the economic performance effects of technological innovation in the planning regions of Germany. The estimation is based on five years' panel data taken every two years, from 2001 to 2009, and takes all the 96 planning regions (except one region with no valid data) of the country. First, I construct cross-sectional data based on the five-year average, and then estimate the extent of the influences technological innovation has on economic growth (PCI, employment, and wage). I use a general regression (OLS) to assess the impact on the economic growth of innovation in planning regions, and then I use the panel data.

I measure technological innovation by R&D intensity, share of researchers, and number of patents applied per 100,000 people; and economic performance by growth of real PCI, employment, and wage growth. My choices of the indicators are based on previous studies. The specification of the empirical model starts with using one of the three economic performance indicators of a planning region: PCI growth. In doing so I use a modified Solow growth model technique (Mankiw, Romer, and Weil, 1992) with a dynamic panel of the following form:

$$\Delta \ln PCI_{i\,t} = (\lambda_1 - 1)\ln PCI_{i\,t-1} + \lambda_2 \ln x_{i\,t}^{'} + \lambda_3 \ln z_{i\,t}^{'} + \lambda_4 yr_{i\,t}^{*} + \ln \psi_i + \ln \varepsilon_{i\,t} \,, i = 1 \, \& \, t = 2, ..., (3.1)$$

Where $\Delta \ln PCI_{i\,t}$ is log difference of PCI[11] over a five-year period in a given planning region; $PCI_{i\,t-1}$ is the log of PCI at the start of that period;

$x_{i\,t}^{'}$ is a set of technological innovation indicators including the share of R&D expenditure, share of R&D employees[12] of the high-tech and knowledge-intensive services, and logs of patent rights applied for per 100,000 people during or at the end of the period; $z_{i\,t}^{'}$ is a set of control variables, such as population density and share of non-R&D employees; $yr_{i\,t}^{*}$ is year dummy that controls shocks; ψ is fixed effect error terms; and $\varepsilon_{i\,t}$ is idiosyncratic error term. Equation (3.1) can be rewritten equivalently in the following way:

$$\ln PCI_{i\,t} = \lambda_1 \ln PCI_{i\,t-1} + \lambda_2 \ln x_{i\,t}^{'} + \lambda_3 \ln z_{i\,t}^{'} + \lambda_4 yr_{i\,t}^{*} + \ln \psi_i + \ln \varepsilon_{i\,t} \,, i = 1 \, \& \, t = 2, ..., (3.2)$$

Here, regional PCI is determined by three variables: true state dependence, a set of explanatory variables (region specific and heterogeneous variables), and error terms. Although the true state dependence (lagged dependent) and other explanatory variables can have dynamic behavior across different years, error terms (time-invariant and time-variant) could exhibit mixed effects. The time-invariant error term is the same all across the years, whereas the idiosyncratic error term does vary across time. The region specific as well as time-invariant error terms should be canceled, because they do not vary throughout the five years. This can be done by first-differencing, and an application of this will result in the following:

$$\Delta \ln PCI_{i\,t} = \lambda_1 \Delta \ln PCI_{i\,t-1} + \lambda_2 \Delta \ln x_{i\,t}^{'} + \lambda_3 \Delta \ln z_{i\,t}^{'} + \lambda_4 \Delta yr_{i\,t}^{*} + \ln \Delta \varepsilon_{i\,t} \,, i = 1 \, \& \, t = 3, ..., (3.3)$$

With the assumption that residuals of level equation are serially uncorrelated as in the following:

$$E(PCI_{i\,t-s}, \Delta\varepsilon_{it}) = 0 \quad t = 3,...,T \ \ and \ \ s \geq 2$$

The above equation, which was introduced by Holtz-Eakin et al. (1988) and later modified by Arellano and Bond (1991), shows estimation equation and moment conditions or first-differenced GMM. After removing regional individual (time-invariant) specific effects through first-differencing, either DGMM or SGMM can be used for estimating regional PCI growth. DGMM has a major drawback if explanatory variables display persistence over time—for example, for variables such as knowledge intensity. In this case, the lagged levels may be very poor instruments for their differences. Blundell and Bond (1998) show that DGMM panel estimator performs poorly when the time series are persistent and small in number, which is a typical problem in empirical growth models. Under such circumstances the coefficient of the lagged dependent variable will exhibit unit root, in which case it results in upward (OLS) bias as explained by Hsiao (1986) or downward (within or FE) bias, as spelled out by (Nickell, 1981). Bias can be detected by an auto-regressive model AR (1), where if the sum of the coefficients of the lagged dependent variable is close to unit root or is near 0, then the specified model is *inconsistent* and, in fact, does not fit the data. Such a problem requires other options.

To reduce the potential bias and imprecisions associated with difference estimator, an alternative is to use SGMM estimator, which is introduced by Arellano and Bover (1995) and later implemented by Blundell and Bond (1998). An advantage of SGMM is that it combines regression equation in first differences, instrumented with lagged levels of regressors, with the regression equation in levels, instrumented with lagged differences of the covariates. Following Blundell and Bond (1998), I supplement moment conditions based on a first-differenced equation with the following level moment conditions:

$$E(\varepsilon_{i\,t}, \Delta PCI_{i\,t-1},) = 0 \quad t = 3,...,T, \qquad E(\varepsilon_{i\,t}, \Delta x_{i\,t-1},) = 0 \quad t = 3,...,T \ \ s \geq 1$$

Blundell and Bond (1998) showed that SGMM increases consistency and efficiency. Usually, the coefficient of the lagged dependent variable or variables in cases of SGMM lies between OLS and within estimator—a phenomenon of consistent estimation. However, SGMM tends to in-

crease the number of instruments as it uses difference and levels at a given time, and it is important to be careful while working on instrumental variables. In this essay, I use two-step SGMM for all three growth models—regional PCI, employment, and wage—because tests of specification for the three models show that two-step SGMM fulfills the criteria and fits the panel data. I do not provide empirical estimation techniques for regional employment growth and regional wage growth models as the procedures are the same as for the regional PCI.

3.5 Data and descriptive statistics

3.5.1 The data

This study uses panel data of five years, taken every two years[13] from 2001 to 2009, where all information is accessed from five sources: Stifterverband[14]; SIAB (1975–2010) of the IAB; the Federal Statistical Office of Germany; Eurostat; and from the Federal Institute for Building, Urban Affairs, and Spatial Development (BBSR). From these data sources, I extract two groups of variables: technological innovation indicators (R&D expenditure, researchers, and patent rights) and planning region economic performance indicators (PCI, employment, and wage). Data on R&D expenditure[15] are obtained from Stifterverband—a business community's innovation agency for the German Science System—and other data, including the number of researchers and patent rights, are accessed from IAB. I construct R&D intensity by taking the share of R&D expenditure from GDP of the corresponding planning region. Similarly, the share of researchers or R&D employees is obtained by taking the total number of full-time researchers of a planning region from the full-time total employees of a corresponding region. The variable patent right represents the logs total patents applied[16] per 100,000 people in any planning region.

   Data on nominal GDP (in millions of Euros), population size, and planning region area coverage are obtained from the Federal Statistical Office of Germany, and information on CPI[17] comes from Eurostat. The nominal GDP data reveal that 412 districts (NUTS3), which represent almost all districts of the country, were found to have valid information. I convert these data into real GDP using a GDP deflator in order to reflect inflation. Further, inflation-adjusted regional GDP is converted into

per capita income (PCI) as it, compared to gross real GDP, better measures economic performance of a planning region.

Information on employment is accessed from SIAB of IAB. These data are administrative, representing 2% of the total employees spanning from 1975 to 2010, with 200,000 employment spells per year. Among other things, the information contains daily wages, working days, and demographic characteristics (vom Berge, König, and Seth, 2013). The data also contain full-time employees who pay social security, public service, or civil service employees; part-time employees; and internship and short-term contract employees. As much of the available information on full-time public and private employees is found to have valid data, I take only full-time employees. The advantage of using full-time employees is that, apart from incorporating the public service and private employees, full-time employees are the ones who are required to work eight hours a day, or 40 hours a week. This helps to identify the wages a full-time employee can get in a day, which is an important aspect of regional labor market analysis and of regional economy. In turn, knowing wages at the regional level is very useful because—unlike PCI, which can be obtained from outside the place where an employee works in as well as from non-employment income—wage is a region-specific variable as it is generated only from within a region where an employee is working. The wage level in each region could indicate the conditions of labor market and of the economy of the particular region. Finally, I use data on the regional accessibility variable, which measures the number of minutes it takes to reach to the next motorway station, from the BBSR of Germany.

All district-level (NUTS3) data are aggregated into planning regions, using a district- planning region matching code system. Since most of the variables of interest are from IAB, which is administrative data, all other non-administrative data obtained from sources other than IAB have been adjusted to fit into administrative data. Based on this, the information used for this essay refers to daily data on June 30 of each year.

3.5.2 Summary statistics

The summary statistics in Table 3.2 show that, on average, the daily per capita income in each of the 96 planning regions is found to be 95 Euros, 1,136 Euros per month, and about 34,082 Euros per year. This figure seems to be well within the range of the PCI of advanced countries. However, contrary to the good average daily PCI, the data shows a big

difference in the distribution of income, because one can find a daily PCI as low as 7,772 Euros and as high as 1,271 Euros, with a standard deviation of 116 Euros. The presence of high PCI inequality in the planning region can be attributed, among other things, to the presence of great differences between the relatively rich West German regions and poor East German regions of the country, which in turn can be explained by the history of the capitalist West Germany and socialist East Germany that spanned from 1950 to 1990. For example, the planning region in Stuttgart, which is in West Germany, has high PCI whereas most regions in East Germany have low PCI. Not only does East Germany have low per capita income, but the supply and demand of the labor market is still in trouble compared to West Germany. Indeed, great inequality in individual PCI across planning regions can affect the extent of technological innovation, a topic that is dealt in the estimation part of the paper.

The data further reveal that there are, on average, over a quarter of a million (281,634.8) full-time employees in each planning region and that the number of these employees appears to be heavily unevenly distributed. Some regions employ as few as 37,336 employees whereas other regions have as many as 1,331,152 employees with a standardized variation of 2,017,372 employees. Such large differences could be explained by a number of factors. First, the geography of some planning regions could be big enough while others can be small. Second, some small regions could have more full-time employees than bigger regions. For example, in urban regions such as Berlin and Hamburg, the number of full-time employees could be more than that of the bigger and less urbanized regions because bigger cities are drivers of the economy and are, therefore, capable of absorbing a larger share of the labor force. Third, some regions are richer than others and are likely to employ more full-time employees than other regions.

The full-time employees are further disaggregated into researchers and non-researchers, where the former are used for measuring the extent of technological innovation. Furthermore, the statistics disclose that, on average, about 5% of the total employees who have university-level education work in R&D activities (mainly in high-tech and knowledge-intensive services), and the remaining 95% of the full-time labor force is engaged in non-research responsibilities, that is, in nonscientific works. Whereas the average share of researchers from the total number of full-time employees is 5%, the minimum share can go as low as 0.5% and the

maximum as high as 38%, indicating that the share of research scientists is highly skewed. It is likely that some regions, like in Bayer (where the headquarters of Telecom, Siemens, and BMW exist) as well as in Baden-Wurttemberg (where Mercedes Benz and Porsche are headquartered), it is natural to expect a large share of researchers, whereas in East Germany, where the level of high-tech and knowledge-intensive services are relatively incomparable to West Germany, the share of researchers would clearly be closer to the minimum. In fact, researchers are not only limited to works of R&D but are also engaged in university-level teaching and consultancy services that are critical for policy formulation.

The average daily wage of full-time employees, which is 85 Euros, is closer to the daily PCI, which is 94 Euros. Nevertheless, although the variation in the daily PCI of individuals is so enormous (as big as 116 Euros), the standardized difference among the daily wages of the employees in a region is small (9 Euros). We should expect this because PCI reveals only distribution of income, as if total GDP is uniformly distributed to the whole population. However, it should also be noted that although the mean of daily PCI is obtained from real gross GDP, daily mean wage is derived from daily median wage.

The information on R&D expenditure demonstrates that, on average, a planning region allocates 2% of total GDP for R&D. This includes expenditures for hiring researchers, buying laboratory equipment, establishing research centers, and for organizing conferences to exchange knowledge. The mean R&D intensity is almost equivalent to the overall R&D intensity of all of Germany, which is about 2.3%. The slight difference comes from the fact that national R&D intensity is based on nominal GDP whereas planning region R&D is based on real GDP. Moreover, I have found that the overall intensity of R&D of each planning region in the country appears to be equivalent to the average of OECD member countries' R&D expenditure. However, it is far behind Finland, which spends about 3.7%, and of Sweden, which invests about 3.5% of total GDP (OECD, 2009). Moreover, I have found that the R&D expenditure per full-time employee is 3,692 thousand Euros, ranging from a minimum of 0.029 thousand euros to a maximum of 83,626 thousand Euros showing significant variations among planning regions.

In addition to R&D expenditure, I accessed patent[18] right information from OECD. Patent rights can be measured in two ways: by the number of patents applied or by patents granted per 100,000 people. The latter is

the preferred approach; however, in the absence of data on the number of patents granted at the planning or NUTS3 level, I use the number of patents applied. The summary statistics show that, on average, each planning region has applied about 224 patents per year and that the minimum and maximum numbers of applications made are 1.2 and 1451 respectively. This could imply that there are significant differences among regions in filing or claiming patent rights, which would also indicate great variations in being able to generate innovations.

Table 3.2
Regional economic performance and technological innovation (Obs. = 480)

Variable	Mean	Std. Dev.	Min	Max
Per capita GDP	94.783	116.614	7.338	1271.536
Employees	279614.7	217036	37336	1331152
Regional wage	85.600	9.408	65.210	115.466
R&D expenditure	.021	.0371	.0001	.426
Share of researchers	.052	.039	.0055	.386
Share of non-researchers	.947	.039	.613	.994
Patents applied per 100,000 pop.	224.067	238.484	1.200	1451.19
R&D expenditure per employee	3.692	6.700	.029	83.626
Population density	3.355	4.227	.665	24.708
Accessibility	16.463	7.353	5	56.6

The log values of some of the variables contain useful insights. On average, the log of population and log of employment are found to have similar values—whereas the former has 13, the latter has 12 (Appendix C2). Moreover, the minimum and maximum log of population and employment exhibit similar figures (10 versus 11), whereas the standard deviations for the two variables are almost equal (0.69). This may indicate that population growth tends to correlate with employment growth (especially if growth of population is mainly attributed to labor force).

Similarly, one would observe that the log of PCI and log of wage each have equivalent values of 4%, on average. However, whereas the distribution of wage in log across planning regions appears to be relatively

uniform, with a standard deviation of 0.1%, the variation of log per capita income seems to be relatively dispersed (0.8% standard deviation). Such distribution could probably emanate from the fact that log of wage is derived from median wage (note that original wage data used for this study is daily wage and not gross wage) while log of PCI is obtained from average PCI. The great differences in the distribution of log of PCI and log of wage is reflected in the minimum and maximum values, in which, whereas log of per capita income has a minimum of 2 and a maximum of 7, the log of wage has minimum of 4 and a maximum of 4.7. These differences can have different implications on regional economy, a topic discussed in the following section. Moreover, I find that the mean log of patent right applications appear to share the pattern of mean log of PCI and log of wage, though there are significant differences in terms of the distribution (minimum and maximum values). The distributions of the planning region economic performance and technological innovation indicators are presented in kernel density functions in Appendices C3-C15 in order to understand the variations of economic performance and innovation indicator variables over the five years.

3.6   Estimation results and discussion

A number of studies have already analyzed the impacts of technological innovation or innovation at firm, sector, or country level. However, there appear to be few or no studies at *meso*[19] level. This part-which is divided into two-presents the estimated results of the impacts of technological innovation on the economic performance of planning regions in Germany. In the first part, I provide interpretations of the five-year average cross-sectional estimation results; and in the second part, the results of the dynamic panel model are thoroughly interpreted. In the first part I attempt to answer the first three questions raised in the introductory part of the essay whereas in the second part I answer all the four research questions. In both parts there are three models: per capita income, employment, and wage growth.

3.6.1 Cross-sectional evidence

In this part, I present the cross-sectional estimation results of the impacts of technological innovation on regional economic performance. I construct cross-section information by taking five years' average of the

panel data and measure technological innovation by share of R&D expenditure, share of researchers, and logs of patent rights applied for per 100,000 people whereas the dependent variable's economic performance is expressed by PCI, employment, and wage growth. Since cross-section analysis can be affected by fixed effect variables such as regional characteristics I include regional dummy to capture region specific differences(Capello and Lenzi, 2013; Stuetzer, Obschonka, Brixy, Sternberg, and Cantner, 2014).

As expected, investment in R&D greatly contributes to the growth of regional PCI, employment, and wage at $p < 1\%$ (Table 3.3). The effect is robust statistically as well as economically and is particularly true for the PCI model, where a 1% increase in the share of the R&D expenditure is found to be responsible for a 0.1% growth of the PCI in each planning region. Moreover, it is identified that employment growth and wage growth, though not as high as PCI, respond to R&D intensity greatly, with the level of the response rate being 0.03% and 0.005% respectively.

There appears to be a theoretical consensus that investment in R&D enhances economy through the improvement of productivity and efficiency of production. The application of this view, however, very much depends on the existence of the right number and mix of researchers. The survey result shows that 5% of the full-time employees are researchers, and the impact of these researchers on the economy of the region is found to be positive. I find that the share of researchers is observed to have great influences on PCI and employment growth at less than 1% level, but it is not robust in wage growth. Indeed, researchers are the experts with comprehensive knowledge, able to generate new ideas, inventions, and innovation such that involvement in these activities tends gradually to increase the productivity of the region. An increase in the productivity of the region usually beefs up the GDP and, as a result, the PCI of a region. When the productivity and GDP grow, then the demand for labor will increase. However, the presence of researchers who have robust effects on PCI and employment does not increase wage level. Two things may account for this. First, because wage is often times fixed by government and does not frequently change, it may seem normal to have an insignificant change due to the presence of research scientists. Recall that most of the employees in this study are public servants whose wages are actually fixed by the government. Second, the presence of a few researchers, which take only 5% of the total observa-

tion, may only increase the wage of few who are engaged in R&D activity and not necessarily the large group of employees, which in turn may prevent overall wage growth impact of researchers from being robust.

Patent right application has a positive influence on the growth of PCI, employment, and wage where the level of the impact is robust at $p < 1\%$. Patents are accompanied by innovation, which brings with it, among others, techniques and mechanisms that increase productivity, introduce organizational efficiency, and provide new marketing strategies where the eventual effect is the overall improvement in growth of the region's GDP. For a 1% rise in logs of patent rights applied for in a region, the PCI of the corresponding region grows by about 0.1%, employment increases by 0.5%, and wage growth increases by 0.04%. This demonstrates that the elasticity of employment growth with respect to patents is more responsive.

Controls including population, R&D expenditure per employee, interaction of the share of R&D expenditure with share of researchers, regional accessibility, interaction of R&D expenditure with patents, and patents applied per employee all have useful implications. As expected, population size and density both have negative but insignificant influence on PCI. The increase in population size, if not a result of the working force, should normally decrease distribution of PCI. The same applies for population density, where an increase in the population per area of the region will result in reducing the distribution of income. On the other hand, whereas population size has a significant positive impact on employment growth, population density still has a negative impact on employment. Moreover, wages are affected positively and considerably by the population size. The different impacts of population size and population density on PCI, employment and wage growth signal that the three regional economic performance variables have different characteristics and features.

Regional accessibility, which measures the number of minutes it takes to go from the centers of a planning region to the next planning region center by car, has no significant impact on any of the planning region economic performance indicators (PCI, employment, and wage growth). The less time it takes to get to the center of the region, the more accessible that region, that is, the easier it is to travel to jobs and the greater the employment opportunities. As expected, accessibility has a negative impact on employment. This implies that the more time it takes to travel

between two consecutive planning region centers; the more it discourages commuters to work in far areas thereby decreasing the number of employees working in distant places. All other controls (interaction of patents with R&D expenditure, patent per employees, and interaction of R&D employees with researchers) have encouraging contributions to the performance of regional economy (PCI, employment and wage growth).

Table 3.3
Five years' average estimates for regional PCI, employment and wages

Explanatories	PCI growth	Employment growth	Wage growth
	ρ (Sta. Err)	ρ (Sta. Err)	ρ (Sta. Err)
Share of R&D exp.	.106 (.038)***	.0347 (.013)***	.005 (.002)**
Share of researchers	.066 (.023)***	.019 (.016)***	.004 (.003)
Log patents applied	.123 (.036)***	.551 (.050)**	.041 (.006)***
Log population size	-.022 (.137)	.246 (.112)**	.047 (.022)***
Population density	-.006 (.021)	-.021 (.018)	.002 (.003)
R&D per employees	.120 (.019)***	-.070 (.094)	
R&D and researchers	2.837 (.753)***		
Log regional accessibility	.122 (.116)	-.070 (.003)	.026 (.018)
Log per capita income			.0495 (.014)***
R&D and patents		.010 (.003)***	.001 (.003)
Patent per employee		9.676 (1.216)***	
Region dummy	included	included	included
Constant	3.303	10.277	3.930
R^2	0.424	0.809	0.687
Adjusted R^2	0.364	0.789	0.655

Standard errors in parentheses, $*p < 0.1$ $**p < 0.05$, $***p < 0.01$

In conclusion, the cross-sectional estimation results, which are based on five years' average of the panel data, show that most of the innovation indicators have a statistically and economically significant impact on PCI, employment, and wage growth. Moreover, most controls are found

to have contributed profoundly to the performance of regional economy. This implies that economic policy making at the regional level should take technological innovation indicators and controls into account to make a planning region competitive. However, because the analysis is based on a general cross-sectional regression, which does not take care of measurement errors and endogeneity, a further analysis using panel data is required. This is dealt in the following section.

3.6.2 Panel evidence

The lag length for regional PCI, employment, and wage[20] growth models are determined by the autoregressive model. I find that for each of these models, the first lag of the dependent variable is proper to use a dynamic (GMM) panel estimator. However, it is not possible to include deeper lags for two reasons. First, for some models, the autoregressive estimation shows that the implementation of deeper lags does not have robust impacts; and second, for other models where deeper lags have significant impact, the use of deeper lags is found to have a substantial effect in reducing the total number of observations. Therefore, I limit the lag length of the dependent variables of the three growth models to lag one.

Like in the cross-section results discussed before, for all three models, the share of R&D expenditure (R&D intensity), share of researchers, and logs of patents applied per 100,000 people are used as explanatory variables to express technological innovation. Furthermore, I include control variables, which are thought to have influence on the economy of planning regions. These variables for the PCI growth model include R&D expenditure per employee (R&DPEM), share of non-researchers (NREARS), population density (POPD), and population (POP); for employment growth model R&DPEM, POPD, and POP; and for wage growth model R&DPEM, PCI, POPD, and POP. Moreover, I include a year dummy in order to control some unobservable shocks. The shocks may be introduction of new tax policy that would affect the employment and/or wage condition of a region or policy interventions on labor market. In all three models, the true state dependence variables have been instrumented by their deeper lags. Furthermore, I check consistency of SGMM by testing whether the coefficient of the lagged dependent variable in the estimated SGMM lies between the coefficients of the same variable in pooled OLS and FE in order to avoid OLS upward (Hsiao, 1986) bias or FE downward bias (Nickell, 1981).

The estimation using the two-step SGMM supports the view that technological innovation or innovation has a positive role in increasing the PCI, employment, and wage growth of a region. The estimation in PCI or growth model shows that the coefficient of lag dependent variable in the estimated two-step SGMM, which is 0.934, lies between pooled OLS, which is 0.984, and that of the coefficients of the within estimator, whose coefficient is 0.125. I have obtained similar results in the employment and wage growth model (Appendix C16).

The estimation result shows that all the true state dependence or lagged dependent variables have positive and robust effects on their respective variables (Table 3.4). For example, the PCI growth of the planning region has been greatly affected by its previous-year income; a region that showed growth in PCI in the previous year has a positive impact on its current-year PCI growth. As can be seen (in Table 3.4) the first lag of PCI has not only an encouraging consequence on current PCI but also is found to be substantial, where the level of the impact is identified to be significant at $p < 1\%$ level. This indicates that regions that have registered a growing PCI in the previous year tend to grow in the current year, and the reverse also holds true. More specifically, a 1% increase in the amount of income in the previous year is responsible for almost a unit (0.9%) of growth in the current year's PCI: showing a one-to-one correspondence between present-year income growths with respect to previous-year income, which further implies that the persistent effects of PCI on income appear to be strong.

In the employment growth model, its true state dependence variable has a positive and huge impact on growth of current employment. I find that the influence of the first lag of employment on current employment growth appears to be positive and robust with the extent of contribution being strong at $p < 0.01$. There are two conditions where an increase in the employment of the previous year could positively affect contemporaneous employment growth: the first is that employment growth in the previous year could have increased productivity of the region where this tends to increase the overall demand for labor in the region. An increase in the productivity of a region will raise the probability of employment, which, in turn, increases overall employment for the current year. The second possibility—an indirect effect—is that an increase in number of employees in past year tends to increase new ideas and knowledge exchange among employees where the interactions could lead to generation

of innovation and other products that are crucial for increasing regional value added as well as productivity. Especially if the increase in the first lag of employment is attributed to the growth in the number of researchers and of creative or innovative people, the effect that these experts can have on growth of current employment is likely to be high. This is because the productivity of researchers who are engaged in the generation of new knowledge and who work in problem-solving areas can essentially beef up the regional economy better than the productivity of non-researchers, eventually increasing current employment.

I further find that the elasticity of current employment with respect to previous-year employment appears to be high because a 1% increase in the first lag of employment is accompanied by a 0.6% growth of present-year employment growth. This indicates that, on average, a planning region that has increased employment by 100% in the last year should expect the current year's employment to grow by 60%; this gives the overall implication that previous-year employment, *ceteris paribus*, has not only positive but also strong influence on current employment performance of a planning region. Unfortunately, there is no way of knowing whether deeper lags of employment (second and third lags) can have similar effects on growth of current employment; it is not possible to use deeper lags due to the possible significant reduction in total observations.

With regard to the wage growth implications of its true state dependence, I find a strong positive impact. In fact, there is a common consensus among labor economists that apart from the extent of technological innovation, variables including schooling, age, gender, experience, and professional background are meaningful factors that explain some of the existing wage differentials among individuals. However, there is much disagreement on the relative importance of each of these variables for earnings. Some studies have shown that wage growth can greatly be affected by the extent of its true state dependence (Heckman and Sedlacek, 1985; Mincer, 1974; Mincer, 1958; Rosen, 1972; Schultz, 1989; Stiglitz, 1975).

The current study reveals that the first lag of median wage has a strong positive implication on the growth of current median wage at $p < 0.01$. The implication is that an increase in the overall growth of regional wage in the previous year provides incentives for employees to work efficiently and to be able to become more productive. This creates an opportunity to have a strong labor market condition with a greater

tendency of attracting more employees from different parts of the country. The accomplishment of different work responsibilities, with more efficiency and productivity, increases the productivity of a region and of the economy of a region. The growth in the productivity of a region, which may be attributed to improvement in wage growth as well as other factors, induces current wage to rise. This is particularly possible in situations where wage increment depends on performance at previous jobs. What I obtained from the five years' longitudinal data is that for a 1% increase in the wages of the previous year, current wages increase by 0.89%—an almost one-to-one growth correspondence. This indicates that wages have tenacious behavior: a region that had relatively high waged in the previous year tends to maintain or even increase wages in the current period, whereas a region with a declined wage record in the previous year is likely to have a drop in wages in the present year. Nevertheless, impacts of persistence need to be interpreted with care, as long as deep lags have not been used.

Most of the *technological innovation indicators* used in this study (R&D intensity, share of researchers, patent rights) and other variables except population size have found to have both positive and substantial effects on PCI, employment, and wage growth. The amount of money invested in R&D (share or intensity of R&D) has a positive contribution on regional PCI, employment, and wage growth. The expenditures made for R&D include funding researchers and hiring experts, expenses for laboratory or pilot surveys, and for buying research materials, among others. The more these activities are undertaken, the greater the probability that technological innovation will emerge because R&D activities are usually accompanied by transfer of knowledge, exchange of ideas, and pooling of new resources.

The positive and strong PCI, employment, and wage growth impact of investment in R&D activities reveals that regions that spend more on R&D, *ceteris paribus*, tend to improve the economic performance of the corresponding region, whereas regions that do not have good R&D financing (or have not been involved in R&D) would rarely be in a position to generate technological innovation and, in turn, will face hardships to boost economic growth. This result supports much of the empirical evidence, including that of Crepon et al. (1998) who found R&D expenditure to be a critical factor for economic growth. It is important to observe that although the effect of the share of R&D expenditure on

regional PCI is positive and significant at $p < 1\%$, the elasticity of planning region PCI with respect to R&D intensity is not as strong as the responsiveness of regional PCI with respect to its first lag. This is because although a 1% increase in the share of R&D intensity is followed by a 0.25% growth in regional PCI, the same increase in the previous-year PCI is followed by a 0.93% growth of PCI.

The *employment growth* effects of R&D intensity appears to be good since, on average, a 100% increase in the share of R&D expenditure is responsible for a 13% increase in employment growth. Nevertheless, compared to how the first lag of employment has affected employment, the impact of R&D intensity on employment growth is smaller because the elasticity of employment with respect to its lag (0.626) is more than with respect to R&D intensity (0.139) showing the less economic significance. Investing in R&D activities also increases *wages*. The effect is notable because a 1% increase in the amount of capital spent on R&D is responsible for a 0.26% increase in regional median wage growth. This shows that median wage grows by about a quarter whenever the share of capital allocated for R&D activities increases by a unit. Nevertheless, the wage growth effects of R&D intensity are not as strong as the first lag of median wage's impact on its wages. This is because elasticity of wage growth with respect to its first lag is 0.894 compared to that of R&D expenditure, which is 0.265.

The positive and enormous contributions of the growth of R&D intensity to wage growth in planning regions provide evidence that investing in R&D is not only an essential part of generating original or incremental technological innovation but also can be seen as a precondition for the improvement of regional economy through raising wages and improving returns of employment income. Increase in wage would, however, have a discouraging effect on employment growth because as the wages of more full-time employees increase, the wage bargaining power of employees gets lower, labor supply gets higher, and labor demand declines. This conventional fact can, however, be reversed through invention of new products and services and generation of original or incremental innovation via R&D, which can increase wages and employment at the same time. This is because the production of new innovations through the application of research tends to increase productivity of a region and thus will be able to absorb more employees with better payments. Moreover, the result that investment in R&D has positive ef-

fects on wage growth also points out that R&D has a positive influence on economic growth because wage is, after all, an indicator of economy. In this case, R&D-induced wage growth and, in turn, economic growth may suggest that regional economic policy makers should consider the multiplier effects of investing in R&D. Of course, as discussed before, institutions (North, 1992) have to be enabling in order to let R&D meet its objectives.

Investment in R&D can be made in basic, experimental, and application studies, which requires qualified researchers trained in different disciplines. Already, a large number of literature shows that R&D intensity has boosted economic performance, especially at firm level, although there are few empirics on how researchers might affect economic performance at the regional level. In order to address this, I include researchers as indicator of technological innovation and estimate their effects on regional PCI, employment, and wage growth. The share of researchers—like the first lag of regional per capita income and share of R&D expenditure (R&D intensity)—have a strong and positive impact on growth of regional PCI at $p < 5\%$. Indeed, I find that a 100% increase in the share of researchers in a planning region induces regional PCI to grow by about 11% (the economic effect, however, seems to be not robust). Researchers provide new ideas and knowledge that can be used to sort out existing economic bottlenecks as they have the ability to identify strategies and proposing solutions. These activities can generate innovations, whether original or incremental, where the cumulative effect would eventually result in the improvement of regional economic growth. Under normal circumstances, more researchers may mean more technological innovation and-in turn-more economic growth. Historically, places that have more researchers tend to innovate more and grow accordingly. For example, the Silicon Valley in the United States has been supporting a higher share of researchers compared to many other parts of the United States, especially in areas of engineering and technology. This has helped the region of Silicon and other surrounding areas to innovate profoundly and, accordingly, to prosper economically. The results of this study support (Schumpeter, 1934) insight that researchers and R&D are the cardinal components of technological innovation and that innovation is an integral part of competitiveness.

The share of researchers also appears to play a crucial role in employment growth. Researchers, who take up 5% of the total full-time

employees, are the kernels of the labor market because they are the ones directly involved in problem-solving activities while generating new concepts and knowledge. This then leads to the production of incremental or original technological innovation and, in turn, brings about growth in total productivity. When the share of these researchers increases by 100%, total employment is observed to grow by slightly more than a quarter (26%). This indicates that growth of employment very much depends on a region's share of researchers, with the implication that economic policy making at the regional level ought to take into account the share of researchers. It should, however, be noted that employment growth is not always an indicator of good economic performance—indeed, the kind of employment, the productivity of each employee, and the type of employment all need to be noted well. A planning region, for example, can be dominated by a small business economy where the existence of many small enterprises could hire many employees; and the growth of employment can, accordingly, be high, but the increase in the number of employees does not necessarily indicate growth in the productivity of small enterprises. The condition can instead be a reflection of the creation of many small businesses at any given time; and under such circumstances, overall employment growth—due to growth of small enterprises—may not necessarily affect the economy of the region. Further, with respect to wage growth, I have found the share of researchers to have a modest positive impact.

A third indicator of technological innovation included in this study is logs of patents *applied per 100,000 people.* Indeed, patent rights have become one of the fundamental innovation indicators following the agreement on Trade-Related Aspects of Intellectual Property Rights (TRIPs) in Uruguay. The theory suggests that intellectual property rights (IPRs), in the form of patents and trademarks, mask works, and trade secrets provide market incentives, which, in turn, stimulate R&D on the part of the private sector. Moreover, patent protection fosters foreign investment, foreign trade, and a flow of new technology. Under protection, the expected rate of return for the devotion of time for energy, money, and time to innovate can be increased (Thompson & Rushing, 1999). Stronger patent protection enables patent holders to obtain higher rent from charging a higher price. In turn, it is likely that this process promotes innovation, thereby raising productivity and economic growth. A large number of literature has shown that patent rights, through stimulation of

R&D, have encouraging effects on the performance of firms, industries, and countries, though there appear to be very few studies in regions (Iwaisako and Futagami, 2013).

The estimation of the present study shows that an increase in the number of patents applied for increases growth of regional PCI and employment at $p < 1\%$ and that of wages at $p < 5\%$. Such results are similar to the contributions of Thompson and Rushing (1999), who found a positive relationship between IPR protection and economic growth for high-income countries, and of Falvey, Foster, and Greenaway (2006), who obtained a positive effect of economic growth of IPR protection for high- and low-income countries but not for middle-income countries. I find that a 1% increase in the number of patents applied for in a region increases PCI growth by about 0.4%, employment growth by about 2%, and wage growth by 0.3%. Under normal circumstances, more patent applications mean more innovation, although application does not necessarily guarantee patent grant. Nevertheless, given the fact that patent application is costly, it is reasonable to expect that regions that apply for patent grants are most likely regions that introduce innovation. If this condition applies, regions that have more patents tend to increase the economic competitiveness as well as growth of the corresponding regions. Compared to the share of researchers, patents right applications have more impact on regional PCI.

The fact that changes in the number of patents have greatly impacted employment performance can be manifested in inventions (Strumsky, Lobo, and van der Leeuw, 2012), such as in new artifacts, devices, processes, or materials (Boot, 2006; Jorgenson, 2001; Khan, 2005). Some inventions—especially patented inventions—leave behind a detailed evidentiary trail; consequently, patenting activity has become a widely used framework for studying knowledge economy (Acs, Anselin, and Varga, 2002; Archibugi, 1992; Bettencourt, Lobo, and Strumsky, 2007; Griliches, 1990; Hall, Jaffe, and Trajtenberg, 2005; Acs and Audretsch, 1989). Patent applications are not necessarily good indicators of innovation. In connection to this, some authors have expressed concerns regarding patent protection and innovative activities.

For instance, Acs et al. (2002) empirically the desirability and limitations of using patent and innovation counts to explain the regional production of new knowledge. Bottazzi and Peri (2003) used European patent data and contended that although a doubling of R&D spending in a

region will greatly increase innovation in that region, this doubling will only have a minuscule impact on innovation in neighboring regions. Gumbau-Albert and Maudos (2009), in their study of differential patenting in Spanish regions, showed that a region's own R&D activities have a positive and robust impact on innovation output, which is measured by number of patents. However, unlike Bottazzi and Peri (2003), these authors note that R&D spillovers are important and that such spillovers result in positive effects on a region's patents. Chapple, Kroll, Lester, and Montero (2011), who used survey data, pointed out that although firms engaged in "green innovation" are likely to respond positively to local and regional markets, this kind of innovation does not necessarily foster regional growth.

In addition to R&D intensity, share of researchers, and patents applied, some control variables (R&D expenditure per employee, share of non-researcher employees, population density, and population size) have been used to examine the extent to which they influence per capita income, employment, and wage growth. The results show that *R&D expenditure per employee* contributes positively to PCI with the level of effect being robust at $p < 0.5\%$. This indicates the possibility of using R&D expenditure per employee[21] as an additional approach in measuring regional economic growth. The share of *non-R&D employees* (NRESEAS), which makes up 95% of total full-time employees, plays a substantial role in impacting PCI. To be more specific, I find that the presence of non-researchers in a planning region increases a region's PCI to grow substantially, with the extent of effect being strong at $p < 1\%$. This proves that researchers who are supposed to have superior knowledge are not the only drivers of innovation and economic growth. Indeed, one does not have to be a researcher to generate new ideas and new knowledge in order to introduce innovation or to become creative. Some of the great innovators of the world, including Bill Gates, are dropouts with minimal or no scientific research experiences. This implies that regional economic policy making should be inclusive, embracing researchers and non-researchers alike as drivers of innovation and, hence, growth.

The result further shows that densely populated regions help increase the economy (PCI) of the region to grow. This may imply that a region with more urban areas is likely to grow faster than a region that is mostly rural. This is because urban areas have more concentrated population than rural areas. The more the population is concentrated, the higher the

specialization of economic activities, which in turn reduces transaction costs, increases resource exchange, eases knowledge exchange, and creates opportunities for innovation. Historically, more populated or urban areas have been centers of civilization and engines of economic growth. The problem, however, is that it is hardly possible to know the quality of labor force that contribute greatly to innovation because it is difficult to precisely know how productive the labor force of the more concentrated region is compared to less concentrated region.

Population size, unlike population density, negatively affects PCI and wage growth where the extent of the impact on the former is found to be robust at $p < 1\%$. Specifically, I find that a 1% increase in the growth of population of a planning region leads to a 0.05% increase in the PCI of the corresponding region. There are three schools of thought on the relationship between population growth and economic growth per head (Blanchet, 1991): the Malthusian position, the transition theory and the revisionist or technological theory. Malthus argues that population growth leads to diminishing resources (whether resources are provided by human effort, such as health facilities, or by nature, such as land, water, and minerals), which would further lead to poverty, degradation, conflict, and reduction, either in the rate of income growth or in population. This theory, seen from population-income relationships, appears to be accepted because it is found that an increase in population results in a decrease in regional PCI (Tiffen, 1995). The transition theory, on the other hand, views is as population growth being driven by level of income. As such, increases in income are initially expected to increase population growth, mainly through lower mortality, but when higher income levels are attained, birth rates decrease and the population stabilize. The theory further argues that an association with increased expenditures on female education tends to decrease fertility rate (and therefore of population growth) as females spend much of their time in school. This theory appears to be practical, at least as of today. Unfortunately, I do not test this theory, as it would be beyond the scope of the study.

The *revisionist theory* claims that population growth provides a means for technological progress; counters the effects of diminishing returns; and leads to income growth through resource discovery, more efficient use of resources, and improvement of resources. Population growth thus increases the chances of generating new ideas and knowledge that are critical for technological innovation, which, in turn, boosts productivity

where this responds positively to income growth. The present study rejects this theory.

To sum up, the contribution shows that the PCI growth of a planning region over the five years is found to be greatly affected by R&D intensity, share of researchers, the number of patent rights applied for, and a set of other control variables. Only population size has a negative effect. Apart from PCI growth, the growth of employment and wages are found to be positively influenced by the above-mentioned technological innovation indicators. The estimation of the study shows that innovation has not only positive but also robust feedback on regional economies, which further informs the need to take into account innovation variables when making regional economic policy and formulating any regional economic development interventions.

A regional economic policy based on comprehensive data of sufficient years and with properly specified models can give the region the opportunity to become more competitive and resilient. The estimation shows that regional PCI, employment, and wage growth models are properly specified. More specifically, the two-step SGMM, which is applied for the three growth models, is found to fit the data because the Arellano-Bond test for the first order AR (1) and second order AR (2) of serial correlations, as well as the Hansen test of over-identification, approve the appropriateness of the model. For the regional PCI model, I find that the Arellano-Bond test for first order AR (1) with $p = 0.046$ and the second order AR (2) with $p = 0.176$ accepts the null hypothesis that error terms are serially uncorrelated. Moreover, the Hansen test of over-identification with $p = 0.077$, which is more than 0.05, shows that the number of instruments used is not correlated with the error terms, are not over-identified, and therefore are valid instruments.

Table 3.4
Two-step SGMM estimates for regional PCI, employment and wage growth

Explanatories	PCI	Employment	Wage
	λ (Std. Err)	λ (Std. Err)	λ (Std. Err)
L1.per capita income	.934 (.009)***		
L1.employment		.626 (.033)***	
L1.wage			.894 (.024)***
Share of R&D exp.	.254 (.075)***	.139 (.022)***	.265 (.054)***
Share of researchers	.114 (.050)**	.263 (.028)***	.023 (.029)
Log patents applied	.041 (.004)***	.018 (.002)***	.003 (.0015)**
Log R&D per employee	.002 (.001)**	.004 (.001)***	.001 (.0003)***
Share of non-researchers	.723 (.087)***		
Population density	.003 (.001)***	.007 (.001)***	.008 (.002)***
Logs of population	-.051 (.005)***	.332 (.033)***	-.003 (.0019)*
Log per capita income			.006 (.001)***
Year dummy	included	included	included
Arellano-Bond AR (1)	z = -1.94 Pr > z = 0.046	z = -2.45 Pr > z = 0.042	z = -4.35 Pr > z = 0.000
Arellano-Bond AR (2)	z = 1.35 Pr > z = 0.176	z = 1.78 Pr > z = 0.076	z = 1.06 Pr > z = 0.287
Hansen overident.	chi2 (40) = 53.31 Prob > chi2 = 0.077	chi2 (44) = 59.84 Prob > chi2 = 0.056	chi2 (24) = 31.09 Prob > chi2 = 0.151
Observations	384	384	384
Planning regions	96	96	96

Standard errors in parentheses, *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

In the employment growth model, AR (1) with $p = 0.046$, which is less than 0.05, and the second order AR (2) with $p = 0.076$, which is more than 0.05, show that there is no serial correlation of error terms. Furthermore, the Hansen test with $p = 0.056$ demonstrates that the number of instruments used is not correlated with error terms. The instruments are not over-identified and are valid instruments. Similarly, a test of the appropriateness of the wage growth model of AR (1) with $p = 0.000$ and AR (2) with $p = 0.287$ accepts the null hypothesis that error terms are uncorrelated. If there were autocorrelations, then the AR (1) p value would have been more than 0.05—and the AR (2) p value should have been less than 0.05. Moreover, the Hansen test ($p = 0.151$) is well beyond the requirement of 0.05. This confirms that the numbers of instruments identified is not correlated with the error term and, therefore, the instruments are valid. Overall, the estimated PCI, employment, and wage growth models confirm that they are properly specified and fulfill SGMM criteria.

3.7   Conclusion

Literature on the economics of technological innovation shows that there is a direct causal link between innovation and economic growth. Innovation is often seen as one of the most important means through which firms, industries, regions, and countries compete and grow, especially in the current era where knowledge economy has become crucial (Mason, Bishop and Robinson, 2009). This view has been translated into economic policy by taking innovation indicators, R&D and patenting, as core drivers of growth.

A large body of literature has investigated the firm or industry (micro level) and country (macro level) performance effects of technological innovation, finding that innovation affects economic performance positively—though such studies do not provide clear evidence on whether the positive effect can be uniform in the short and long term. Besides, one would barely find rigorous study that assesses the influences of innovation on economic performance at regional level due to (a) paucity of innovation data indicators at the regional level and (b) regions compared to national economies used to have less recognition. However, due to globalization and the advancement of information communication technology, regions are no longer unrecognized and in fact have increasingly become crucial economic entities of the national and global economy.

This study has attempted to analyze the implications of TI on the economic performance of planning regions in Germany. The analysis, which is based on five-year panel data that covers whole regions of the country, measures technological innovation by R&D expenditure, share of researchers, and number of patents applied for whereas regional economic performance is measured by growth of PCI, employment, and wage growth. The study is undertaken for planning instead of administrative regions. This is because the former compared to the latter can be regarded as functional units in the sense of travel-to-work areas and because planning regions account for economic interactions between districts. All data of the study are accessed from SIAB of IAB, Stifterverband, the Federal Statistical Office of Germany, and from Eurostat.

The econometric analysis of the data is done in two parts. The first part provides estimation results of the five-year average cross-section of the panel data using a general regression, and in the second part, I use an SGMM model for the five-year panel data. The analysis using the cross-section regression and SGMM estimator shows that most of the technological indicators (R&D expenditure, share of researchers, and patents applied for) have positive and robust impacts on the growth of regional PCI, employment, and wages. However, the elasticity with which PCI, employment, and wage growth respond to R&D expenditure, share of scientific researchers, and patents applied for differs, implying that the economic implications of the technological indicators do have different effects on various economic performance parameters of a region. The share of non-researchers also has positive and robust implications for each of the economic performance indicators, which may show that technological innovation and, hence, economic growth of regions, particularly the PCI growth of regions, can be factored not only by using the share of researchers who are considered to be inventors and innovators but also by using non-researchers who are not necessarily expected to be scientists. As anticipated, only population size has a strong negative impact on growth of PCI and wage region when panel estimation is used. In the cross-section estimation, too, population size has a negative and substantial impact on PCI growth but has a positive influence on growth of employment and wages. This paper concludes that technological innovation can be explained by factors other than R&D and patents such as by share of researchers, non-researchers, R&D expenditure per employee, and patents applied for per employee. These variables do meas-

ure the condition of technological innovation in a region and, hence, the economic performance of regions. Also, non-technological innovation indicators such as population size, regional accessibility, and population density do have implications on the PCI, employment growth, and wage growth of a planning region.

Notes

[1] It is the implementation of a new or significantly improved product (good or service) or process, a new marketing method, or a new organizational method in business practices, workplace organization, or external relations (OECD, 2005). Innovation is all about making something new and should include three elements: generate or realize new goods, services, or ideas (invention and creativity); develop these goods, services, or ideas into a reality or product (realization); and implement and market the new goods, services, or ideas.

[2] In this essay, unless otherwise stated, exclusively technical change, technological innovation, and innovation refer to the same thing. In fact, technical change involves a broader concept consisting of invention, innovation, and diffusion. The diffusion part of technical change is not at all the focus of this study; under such circumstances, throughout this paper, innovation, technical change, or technological innovation only refers to the invention and/or innovation parts. There is no innovation without invention, and if it exists, it should be only incremental innovation. At the same time it is would be difficult to think of invention without innovation. The fundamental difference between invention and innovation is that while the former deals with the generation of new or original goods or services, innovation, which can also be interpreted as original innovation or incremental innovation, should not necessarily produce only new or original products.

[3] There is ample theoretical evidence demonstrating that no nation in the world has developed without being technologically knowledgeable and that many of the developed countries we know today have profoundly produced and used technology, resulting in the positive impact on economic performance. In this case it sounds reasonable to argue that technology, together with science, can be taken as a precondition for the advancement as well as for the continuation of economic improvements in the long run. Regions also require good technology and science to have competent economic growth and continuous development. However, technology is one of the many factors able to affect the economic scenario of the region, along with institutions, governance, and absorption capability, which can affect the economic fate of regions.

[4] The role of discovery is enormous. It enables the invention of new products; it increases productivity, efficiency, and precisions and creates a condition for continuous improvement of innovation.

[5]R&D expenditure and number of patent rights per 100,000 people are the fundamental indicators of technological innovation. The use of the same indicators for innovation and TI often confuses the difference between innovation & TI. However, while innovation uses both tangible (product innovation) and intangible (market and organizational) indicators TI does use tangible inputs to generate technological outputs. Besides, although TI is a precondition for innovation, the reverse doesn't necessarily hold.

[6]Detailed analysis of the limitations and advantages of using cross-section regression versus panel regression in growth models is presented in Caselli, Esquivel, and Lefort (1996).

[7]R&D is an activity involving significant transfers of resources among units, organizations, and sectors, especially between government and other performers. It is important for science policy advisors and analysts to know who finances R&D and who performs it.

[8]R&D outlay includes the total amount of capital invested for any kind of research and development related activities, regardless of whether the expenditure is made in private, public, or university organization. R&D outlay and intramural R&D expenditures are all expenditures for research and development (R&D) performed within a statistical unit or sector of the economy during a specific period, whatever the source of funds. The procedure for obtaining intramural R&D expenditure at a regional level is as follows: first, identify the intramural expenditure on R&D performed by each statistical unit; second, identify the sources of funds for these intramural R&D expenditures as reported by the performer; and finally, aggregate the data by region of performance and sources of funds to derive significant regional totals to identify the extramural R&D expenditures of each statistical region.

[9]Certainly, differences in technological gaps are likely to create differences in the economic conditions of the countries considered in the study. However, his study doesn't indicate to what extent differences in cumulative causations affects technological change and the economic development of the countries included in the survey. For questions of this type, rich data with probably dynamic panel model is needed to examine the relationships which eventually can provide better pictures of the relationships.

[10]It is, however, hardly possible to have a clear conclusion on the positive effects of technological innovation on employment growth because technology usually favors the jobs of those individuals with high-level training possibly obtained at the university level and, in particular, in science, technology, and related skills. Indeed, a number of studies have demonstrated that the proliferation of technology in advanced countries has decreased the employment opportunity of low-skilled people and have displaced many for unemployment.

[11] The per capita income refers to the adjusted or real per capita income, which takes inflation into account.

[12] The European Commission takes employment in high-tech sectors (high-tech manufacturing and high-tech knowledge-intensive services) as percentage of total employment as one of the fundamental indicators for measuring the level of technology in a region. Actually, this measurement sometimes creates confusion with the human resource component, which is also used as an indicator of technological change.

[13] Because R&D expenditure is not available in every year; every two years' data is used for this study.

[14] This works with universities, institutes, and companies, allowing homegrown talent to be developed to its full potential and new ideas to be brought to fruition. It acts as a major driving force behind the cooperation between industry and science and behind the dialogue between academia and the general public.

[15] Gross domestic expenditure on R&D is the total intramural expenditure on R&D performed in the subnational territory (region) during a given period (*Frascati Manual*, Section 6.7.1 and Section 6.6). Intramural expenditures are all expenditures for R&D performed within a statistical unit or sector of the economy during a specific period, whatever the source of funds (*Frascati Manual*, Section 6.2). The gross domestic expenditure in R&D is disaggregated in four sectors: business enterprise, government, higher education, and private nonprofit. R&D intensity is defined as the ratio between R&D expenditures and GDP.

[16] The numbers of patents applied are not necessarily the same as the number of patents granted, because some of the patents may not pass all the criteria. As such, it is almost always the case that the number of patents applied for are more than the number of patents granted. Accordingly, studies that measure technological innovation using patents applied instead of patents granted will have a much inflated data. As a result the number of grants provided tends to provide a better picture of technological performance than the number of grants applied could measure innovation. However, the fact that applications for patent rights are costly in money and time and also have to pass through stringent screening processes implies that most applied patents would get grants. Although data on patents applied is relatively accessible, this is not the case for patents granted.

[17] Real GDP, which can be derived from nominal GDP through the adjustment of inflation, can be done in two ways: the first is by dividing nominal GDP by GDP deflator while the second is by dividing GDP at current prices by consumer price index. The GDP deflator and CPI diverge to some extent because whereas GDP deflator includes goods and services produced domestically CPI includes domestically made and imported goods and services. Because CPI takes into account inflation, which is attributed from a rise in the prices of goods and services

produced domestically as well as prices affected from outside, it seems reasonable to use CPI as a better proxy for converting current-price GDP into constant-price GDP.

[18]A patent is an exclusive right granted for an invention, which is a product or a process that provides a new way of doing something or offers a new technical solution to a problem. A patent provides protection for the invention to the owner of the patent. The protection is granted for a limited period, generally 20 years. The Patent Co-operation Treaty (PCT) is an international treaty, administered by the World Intellectual Property Organization (WIPO), among more than 125 countries. The PCT makes it possible to seek patent protection for an invention simultaneously in each of a large number of countries by filing a single "international" patent application instead of filing several separate national or regional patent applications (OECD, 2009).

[19]Whereas national and firm-level analysis of innovation-induced employment growth are respectively represented as macro and micro, any level of analysis that exists between the two levels are considered in this particular essay as meso-level analysis. These include planning regions which usually include city and some rural areas or administrative regions (NUTS2 and NUTS3). Empirical studies that analyze innovation-labor market growth relationship appear to focus either at the firm level or national level. This brought questions of why regional-level analysis remains to be a less studied area where the central objective of our paper is to address this gap.

[20]Unlike in the regional per capita and employment growth models, which we have discussed and where per capita and employment have been used in their average values, in the wage growth model, wage represents median wage. The advantage of using median wage over average wage is that median places equal weight on all observations and is less affected by the presence of extreme values (outliers).

[21]An interesting aspect of using R&D expenditure per R&D employee as an indicator of technological innovation and thereby examining the implications on GDP per capita growth is that it is possible to know precisely the share of R&D intensity per researcher, both of which are crucial measures of innovation. Because R&D intensity and researchers have multiplier effects, the use of both in measuring economic performance would even tend to provide estimations that are more precise than R&D expenditure per GDP or R&D expenditure per total number of employees. We suggest future research to use R&D expenditure per researcher.

References

Abel, A., & Blanchard, O. (1983). An inter-temporal model of saving and investment. *Econometrica*, *51*(3), 675–692.

Abramovitz, M. (1956). *Resource and output trends in the United States since 1870*. NBER Occasional paper, no 52.

Acs, Z., Anselin, L., & Varga, A. (2002). Patents and innovation counts as measures of regional production of new knowledge. *Research Policy*, *31*(7), 1069–1085.

Acs, Z., & Audretsch, D. (1989). Patents as a measure of innovative activity. *Kyklos*, *42*(2), 171–180.

Aghion, P., & Howitt, p. (1992). A model of growth through creative destruction. *Econometrica*, *60*(2), 323–351.

Ahn, S., & Schmidt, P. (1995). Efficient estimation of models for dynamic panel data. *Journal of Econometrics*, *68*(1), 5–27.

Aizcorbr, A., Moylan, C., & Robbins, C. (2009). Toward better measurement of innovation and intangibles, *89*(1), 1–10.

Almeida, P., & Kogut, B. (1999). Localization of knowledge and the mobility of engineers in regional networks. *Management Science*, *45*(7), 905–917.

Alvarez, R., & López, R. (2005). Exporting and performance: Evidence from Chilean plants. *Canadian Journal of Economics*, *38*(4), 1384–1400.

Amabile,, T., & Conti, R. (1999). Changes in the work environment for creativity during downsizing. *Academy of Management Journal*, *42*(6), 630–640.

Amabile,, T. M., Conti, R., Coon, H., Lazenby, J., & Herron, M. (1996). Assessing the work environment for creativity. *Academy of Management Journal*, *39*(5), 1154–1184.

Andersen, K., Hansen, H., Isaksen, A., & Raunio, M. (2010). Nordic city regions in the creative class debate-putting the creative class thesis to a test. *Industry & Innovation*, *17*(2), 215–240.

Anderson, T., & Hsiao, C. (1981). Estimation of dynamic models with error components. *Journal of the American Statistical Association*, *76*(375), 598–606.

Anderson, T., & Hsiao, C. (1982). Formulation and estimation of dynamic models using panel data. *Journal of Econometrics*, *18*(1), 47–82.

Anselin, L., Varga, A., & Acs, Z. (1997). Local geographic spillovers between university research and high technology innovations. *Journal of Urban Economics*, *42*(3), 422–448.

Antonelli, G., & Liso, N. (1997). *Economics of structural and technological change*. (1st ed.). Routledge.

Archibugi, D. (1992). Patenting as an indicator of technological innovation: A review. *Science and Public Policy*, *19*(6), 357–368.

Archibugi, D., & Michie, J. (Eds.). (1998). *Trade, growth, and technical change*. New York: (1st ed.). Cambridge University Press.

Arellano, M. (2003). *Panel data econometrics*. (1st ed.). Oxford University Press.

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies*, *58*(2), 277–297.

Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics*, *68*(1), 29–51.

Arrow, K. (1962). The economic implications of learning by doing. *The Review of Economic Studies*, *29*(3), 155–173.

Asheim, B., & Hansen, H. (2009). Knowledge bases, talents, and contexts: On the usefulness of the creative class approach in Sweden. *Economic Geography*, *85*(4), 425–442.

Audretsch, D. B. (1995). *Innovation and industry evolution*. (1st ed.). Cambridge, Mass.: MIT Press.

Audretsch, D. B., Keilbach, M. C., & Lehmann, E. (2006). *Entrepreneurship and economic growth*. (1st ed.). Oxford University Press.

Audretsch, D., & Feldman, M. (1996). Innovative clusters and the industry life cycle. *Review of Industrial Organization*, *11*(2), 253–273.

Audretsch, D., & Vivarelli, M. (1996). Determinants of new-firm startups in Italy. *Empirica*, *23*(1), 91–105.

Aw, B. Y., Roberts M., J., & XU D., Y. (2009). R&D investment, exporting and productivity dynamics. *American Economic Review*, *101*(4), 1312–1344.

Baldwin, J., & Lin, Z. (2002). Impediments to advanced technology adoption for Canadian manufacturers. *Research Policy*, *31*(1), 1–18.

Ball, J., & Skeoch, N. (1981). *Inter-plant comparisons of productivity and earnings* (1st edition.). Unit for Manpower Studies, Dep. of Employment, London, 1st edition.

Ball, J., Zhu, Z., & Xie, H. (2004). Measuring intellectual capital: A new model and empirical study. *Journal of Intellectual Capital*, *5*(1), 195–212.

Baltagi, B. H. (2013). *Econometric analysis of panel data*. (5th ed.). John Wiley & Sond.Ltd.

Bamberry, G. (2006). The influence of technology on regional development: Case studies from the Riverina region, *12*(2), 173–190.

Barge-Gil, A. (2010). Cooperation-based innovators and peripheral cooperators: An empirical analysis of their characteristics and behavior. *Technovation*, *30*(3), 195–206.

Basu, S. (1996). Procyclical productivity: Increasing returns or cyclical utilization? *The Quarterly Journal of Economics*, *111*(3), 719–51.

Baumol, W. (1990). Entrepreneurship: Productive, unproductive, and destructive. *Journal of the Political Economy*, *98*(5), 893–921.

Becker, G. (1960). Underinvestment in college education? *The American Economic Review*, *50*(2), 346–354.

Becker, G. (1962). Investment in human capital: A theoretical analysis. *Journal of Political Economy*, *70*(5), 9–49.

Becker, G. (1993). *Human capital: A theoretical and empirical analysis with special reference to education*. Chicago: University of Chicago Press, 3rd edition.

Becker, G. S. (1960). Underinvestment in College Education? *The American Economic Review*, *50*(2), 346–354.

Belderbos, R., Carree, M., & Lokshin, B. (2006). Complementarity in R&D cooperation strategies. *Review of Industrial Organization*, *28*(4), 401–426.

Bessen, J. (2002). Technology adoption costs and productivity growth: The transition to information technology. *Review of Economic Dynamics*, *5*(2), 443–469.

Bettencourt, L., Lobo, J., & Strumsky, D. (2007). Invention in the city: Increasing returns to patenting as a scaling function of metropolitan size. *Research Policy*, *36*(1), 107–120.

Bierly, P., & Chakrabarti, A. (1996). Generic knowledge strategies in the U.S. pharmaceutical industry. *Strategic Management Journal*, *17*(Winter), 123–135.

Blanchet, D. (1991). On interpreting observed relationships between population growth and economic growth: A graphical exposition. *Population and Development Review*, *17*(1), 105–114.

Blanchflower, D., & Burgess, S. (1998). New technology and Jobs: Comparative evidence from a two Country study. *Economics of Innovation and New Technology*, *5*(2-4), 109–138.

Blanchflower, D., & Oswald, A. (1994). *The wage curve.* (1st ed.). MIT Press.

Blechinger, D., Kleinknecht, A., Licht, G., & Pfeiffer, F. (1998). The impact of innovation on employment in Europe: An analysis using CIS data. ZEW-Center for European Economic Research.

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, *87*(1), 115–143.

Blundell, R., Griffith, R., & Windmeijer, F. (2002). Individual effects and dynamics in count data models. *Journal of Econometrics*, *108*(1), 113–131.

Boot, M., & Council on Foreign Relations. (2007). *War made new: weapons, warriors, and the making of the modern world.* New York, N.Y.: Gotham Books.

Booth, A., & Snower, D. (1996). *Acquiring skills: Market failures, their symptoms and policy responses.* Cambridge University Press.

Boschma, R., & Fritsch, M. (2009). Creative class and regional growth: Empirical evidence from seven European Countries. *Economic Geography*, *85*(4), 391–423.

Bottazzi, G., Dosi, G., Lippi, M., Pammolli, F., & Riccaboni, M. (2001). Innovation and corporate growth in the evolution of the drug industry. *International Journal of Industrial Organization*, *19*(7), 1161–1187.

Bottazzi, L., & Peri, G. (2003). Innovation and spillovers in regions: Evidence from European patent data. *European Economic Review*, *47*(4), 687–710.

Brouwer, E., Kleinknecht, A., & Reijnen, J. (1993). Employment growth and innovation at the firm level. *Journal of Evolutionary Economics*, *3*(2), 153–159.

Brown, J. (1969). Shift and share projections of regional economic growth: An empirical test. *Journal of Regional Science*, *9*(1), 1–18.

Burnside, C., Eichenbaum, M., & Rebelo, S. (1995). Capacity utilization returns to scale. In B. Bernanke & J. Rotemberg (Eds.), *NBER Macroeconomics Annual* (Vol. 10, pp. 67–110).

Cainelli, G., Evangelista, R., & Savona, M. (2004). The impact of innovation on economic performance in services. *The Service Industries Journal, 24*(1), 116–130.

Cainelli, G., Evangelista, R., & Savona, M. (2006). Innovation and economic performance in services: A firm-level analysis. *Cambridge Journal of Economics, 30*(3), 435–458.

Cameron, A. C., & Trivedi, P. K. (2010). *Microeconometrics using Stata.* (Revised ed.). Stata Press.

Capaldo, A., & Petruzzelli, A. (2011). In search of alliance-level relational capabilities: Balancing innovation value creation and appropriability in R&D alliances. *Scandinavian Journal of Management, 27*(3), 273–286.

Capello, R., & Lenzi, C. (2013). Innovation and employment dynamics in European regions. *International Regional Science Review, 36*(3), 322–353.

Cardinal, L., Alessandri, T., & Turner, S. (2001). Knowledge codifiability, resources, and science-based innovation. *Journal of Knowledge Management,* (2), 195–204.

Carroll, G. R., & Hannan, M. T. (2004). *The demography of corporations and industries.* (1st ed.). Princeton University Press.

Caselli, F., Esquivel, G., & Lefort, F. (1996). Reopening the convergence debate: A new look at cross-country growth empirics. *Journal of Economic Growth, 1*(3), 363–389.

Cassiman, B., & Golovko, E. (2011). Innovation and internationalization through exports. *Journal of International Business Studies, 42*(1), 56–75.

Castellacci, F. (2002). Technology gap and cumulative growth: Models and outcomes. *International Review of Applied Economics, 16*(3), 333–346.

Castillo, V., Maffioli, A., Rojo, S., & Stucchi, R. (2014). The effect of innovation policy on SMEs' employment and wages in Argentina. *Small Business Economics, 42*(2), 387–406.

Chapple, K., Kroll, C., Lester, W., & Montero, S. (2011). Innovation in the green economy: An extension of the regional innovation system model? *Economic Development Quarterly, 25*(1), 5–25.

Choi, S. B., & Williams, C. (2014). The impact of innovation intensity, scope, and spillovers on sales growth in Chinese firms. *Asia Pacific Journal of Management, 31*(1), 25–46.

Christensen, C., & Bower, J. (1996). Customer power, strategic investment, and the failure of leading firms. *Strategic Management Journal, 17*(3), 197–218.

Christensen, C., & Raynor, M. (2010). *The innovator's solution: Creating and sustaining successful growth.* Boston, Mass: Harvard Business School Press.

Chudnovsky, D., Lopez, A., & Pupato, G. (2006). Innovation and productivity in developing countries: A study of Argentine manufacturing firms' behavior (1992-2001). *Research Policy*, *35*(2), 266–288.

Cingano, F., & Schivardi, F. (2004). Identifying the source of local productivity growth. *Journal of the European Economic Association*, *2*(4), 720–744.

Clark, J., & Guy, K. (1998). Innovation and competitiveness: A review. *Technology Analysis & Strategic Management*, *10*(3), 363–395.

Coad, A., & Rao, R. (2011). The firm-level employment effects of innovations in high-tech US manufacturing industries. *Journal of Evolutionary Economics*, *21*(2), 255–283.

Colombelli, A., Haned, N., & Le Bas, C. (2013). On firm growth and innovation: Some new empirical perspectives using French CIS (1992–2004). *Structural Change and Economic Dynamics*, *26*(September), 14–26.

Conlisk, J. (1967). A Modified neoclassical growth model with endogenous technical change. *Southern Economic Journal*, *34*(2), 199–208.

Conlisk, J. (1969). A neoclassical growth model with endogenously positioned technical change frontier. *Economic Journal*, *79*(314), 348–62.

Cooke, P. (2002). *Knowledge economies: Clusters, learning and cooperative advantage.* London; New York: Routledge.

Crepon, B., Duguet, E., & Mairesse, J. (1998). Research, innovation and productivity: An econometric analysis at firm level. *Economics of Innovation and New Technology*, *7*(2), 115–158.

Currid-Halkett, E., & Stolarick, K. (2013). Baptism by fire: Did the creative class generate economic growth during the crisis? *Cambridge Journal of Regions, Economy and Society*, *6*(1), 55–69.

Czarnitzki, D., & Thorwarth, S. (2012). Productivity effects of basic research in low-tech and high-tech industries. *Research Policy*, *41*(9), 1555–1564.

Damanpour, F., Walker, R., & Avellaneda, C. (2009). Combinative effects of innovation types and organizational performance: A longitudinal study of service organizations. *Journal of Management Studies*, *46*(4), 650–675.

Del Monte, A., & Papagni, E. (2003). R&D and the growth of firms: empirical analysis of a panel of Italian firms. *Research Policy*, *32*(6), 1003–1014.

Dixit, A., & Pindyck, R. (1994). *Investment under uncertainty.* Princeton, New Jersy: Princeton University Press,1st edition.

Dosi, G. (1988). Sources, procedures, and microeconomic effects of innovation. *Journal of Economic Literature*, *26*(3), 1120–1171.

Dosi, G., Marsili, O., Orsenigo, L., & Salvatore, R. (1995). Learning, market selection and the evolution of industrial structures. *Small Business Economics*, *7*(6), 411–436.

Edquist, C., Hommen, L., & McKelvey, M. (2001). *Innovation and employment: Process versus product innovation*. Edward Elgar Publishing,1st edition.

Enright, M. (2003). Regional clusters: What we know and what we should know. In J. Bröcker, D. Dohse, & R. Soltwedel (Eds.), *Innovation Clusters and Interregional Competition* (pp. 99–129). Springer Berlin Heidelberg.

Entorf, H., & Pohlmeier, W. (1987). *Employment, innovation and export activity: Evidence from firm-level data*. Oxford University.

Eurostat. (1996). *The regional dimension of R & D and innovation statistics: regional manual*. Luxembourg: Office for Official Publications of the European Communities.

Even, W., & Macpherson, D. (2003). The wage and employment dynamics of minimum wage workers. *Southern Economic Journal*, *69*(3), 676–690.

Fabricant, S. (1959). *Basic facts on productivity change*. NBER,1st edition.

Fagerberg, J., & Sapprasert, K. (2010). *Innovation: Exploring the knowledge base*. Working Papers on Innovation Studies, no 20100616.

Fagerberg, J., & Verspagen, B. (2009). Innovation studies-The emerging structure of a new scientific field. *Research Policy*, *38*(2), 218–233.

Falk, M. (2007). R&D spending in the high-tech sector and economic growth. *Research in Economics*, *61*(3), 140–147.

Falvey, R., Foster, N., & Greenaway, D. (2006). Intellectual property rights and economic growth. *Review of Development Economics*, *10*(4), 700–719.

Flinn, C. (2006). Minimum wage effects on labor market outcomes under search, matching, and endogenous contact rates. *Econometrica*, *74*(4), 1013–1062.

Flinn, C. J. (2010). *The minimum wage and labor market outcomes* (1st ed.). (1st ed.). MIT Press.

Florida, R. (2002). Bohemia and economic geography. *Journal of Economic Geography*, *2*(1), 55–71.

Florida, R. (2002). *The rise of the creative class: And how It's transforming work, leisure, community and everyday life*. Basic Books,1st edition.

Florida, R. (2003). Cities and the creative class. *City & Community*, *2*(1), 3–19.

Florida, R. (2005). *Cities and the creative class.* (1st ed.). Routledge.

Florida, R. (2007). *The flight of the creative class: The new global competition for talent.* (1st ed.). Collins.

Florida, R., Mellander, C., & Stolarick, K. (2008). Inside the black box of regional development-human capital, the creative class and tolerance. *Journal of Economic Geography*, *8*(5), 615–649.

Florida, R., Mellander, C., & Stolarick, K. (2010). Talent, technology and tolerance in Canadian regional development. *Canadian Geographer*, *54*(3), 277–304.

Freeman, C., & Soete, L. (1997). *The economics of industrial innovation.* (3rd ed.). Routledge.

Fritsch, M., Brixy, U., & Falck, O. (2006). The effect of industry, region, and time on new business survival-A multi-dimensional analysis. *Review of Industrial Organization*, *28*(3), 285–306.

Fritsch, M., & Schindele, Y. (2011). The contribution of new businesses to regional employment-An empirical analysis. *Economic Geography*, *87*(2), 153–180.

Fritsch, M., & Stützer, M. (2008). The Geography of Creative People in Germany. MPRA Paper. Retrieved November 21, 2013, from http://mpra.ub.uni-muenchen.de/21965/

Gabe, T., Florida, R., & Mellander, C. (2013). The Creative Class and the crisis. *Cambridge Journal of Regions, Economy and Society*, *6*(1), 37–53.

García-Manjón, J., & Romero-Merino, E. (2012). Research, development, and firm growth. Empirical evidence from European top R&D spending firms. *Research Policy*, *41*(6), 1084–1092.

Gault, F. (2013). *Innovation strategies for a global economy.* Edward Elgar Publishing,1st edition.

Gault, F. (2013). The Oslo Manual. In *Handbook of innovation indicators and measurement.* Edward Elgar Publishing.

Geroski, P., Machin, S. ., & Walters, C. (1997). Corporate growth and profitability. *The Journal of Industrial Economics*, *45*(2), 171–189.

Geroski, P., Machin, S., & Van Reenen, J. (1993). The profitability of innovating firms. *The RAND Journal of Economics*, *24*(2), 198–211.

Geroski, P., & Mazzucato, M. (2002). Learning and the sources of corporate growth. *Industrial and Corporate Change*, *11*(4), 623–644.

Glaeser, E. (2005). Edward L. Glaeser, Review of Richard Florida's The Rise of the Creative Class. *Regional Science and Urban Economics*, *35*(5), 593–596.

Glaeser, E., Kallal, H., Scheinkman, J., & Shleifer, A. (1992). Growth in cities. *Journal of Political Economy*, *100*(6), 1126–52.

Gloet, M., & Terziovski, M. (2004). Exploring the relationship between knowledge management practices and innovation performance. *Journal of Manufacturing Technology Management*, *15*(5), 402–409.

Gort, M., & Klepper, S. (1982). Time paths in the diffusion of product innovations. *Economic Journal*, *92*(367), 630–53.

Greenan, N., & Guellec, D. (2000). Technological innovation and employment reallocation. *LABOUR*, *14*(4), 547–590.

Greenhalgh, C., & Rogers, M. (2010). *Innovation, intellectual property and economic growth*. Princeton: Princeton University Press.

Griffith, R., Huergo, E., Mairesse, J., & Peters, B. (2006). Innovation and productivity across four European Countries. *Oxford Review of Economic Policy*, *22*(4), 483–498.

Griliches, Z. (1957). Hybrid Corn: An exploration in the economics of technological change. *Econometrica*, *25*(4), 501–522.

Griliches, Z. (1979). Issues in assessing the contribution of research and development to productivity growth. *Bell Journal of Economics*, *10*(1), 92–116.

Griliches, Z. (1990). Patent statistics as economic indicators: A survey. *Journal of Economic Literature*, *28*(4), 1661–1670.

Griliches, Z. (1995). R&D and productivity : econometric results and measurement issues.

Griliches, Z. (1995). R&D and productivity : Econometric results and measurement issues. In *Handbook of the economics of innovation and technological change* (1st ed., pp. 52–89). Blackwell Publishing Ltd.

Grossman, G. (1993). *Innovation and Growth in the Global Economy*. MIT Press.

Grossman, G., & Helpman, E. (1991). Quality ladders in the theory of growth. *The Review of Economic Studies*, *58*(1), 43–61.

Grupp, H. (1995). Science, high technology and the competitiveness of EU countries. *Cambridge Journal of Economics*, *19*(1), 209–223.

Guan, J., & Chen, K. (2010). Measuring the innovation production process: A cross-region empirical study of China's high-tech innovations. *Technovation*, *30*(5–6), 348–358.

Gumbau-Albert, M., & Maudos, J. (2009). Patents, technological inputs and spillovers among regions. *Applied Economics*, *41*(12), 1473–1486.

Hall, B. ., & Mairesse, J. (2006). *Empirical studies of innovation in the knowledge driven economy* (No. 12320). National Bureau of Economic Research.

Hall, B. H., Lotti, F., & Mairesse, J. (2012). *Evidence on the impact of R&D and ICT investment on innovation and productivity in Italian firms* (No. 18053). NBER Working Paper.

Hall, B., Jaffe, A., & Trajtenberg, M. (2005). Market value and patent citations. *RAND Journal of Economics*, *36*(1), 16–38.

Hall, R. (1975). Review of schooling, experience, and earnings by Jacob Mincer. *Journal of Political Economy*, *83*(2), 444–446.

Hamermesh, D., & Pfann, G. (1996). Adjustment costs in factor demand. *Journal of Economic Literature*, *34*(3), 1264–1292.

Hansen, H., & Niedomysl, T. (2009). Migration of the creative class: Evidence from Sweden. *Journal of Economic Geography*, *9*(2), 191–206.

Harkema, S. (2003). A complex adaptive perspective on learning within innovation projects, *10*(6), 340–346.

Harrison, R., Jaumandreu, J., Mairesse, J., & Peters, B. (2008). *Does innovation stimulate employment? A firm-level analysis using comparable micro-data from four European countries* (NBER Working Paper No. 14216).

Heckman, J., & Sedlacek, G. (1985). Heterogeneity, aggregation, and market wage functions: An empirical model of self-Selection in the labor market. *Journal of Political Economy*, *93*(6), 1077–1125.

Henderson, R. (1993). Underinvestment and incompetence as responses to radical innovation: Evidence from the photolithographic alignment equipment industry. *The RAND Journal of Economics*, *24*(2), 248–270.

Hirschman, A. (1957). Investment policies and "Dualism" in underdeveloped Countries. *The American Economic Review*, *47*(5), 550–570.

Holtz-Eakin, D., Newey, W., & Rosen, H. S. (1988). Estimating vector autoregressions with panel data. *Econometrica*, *56*(6), 1371.

Hsiao, C. (1986). *Analysis of panel data.* (1st ed.). Cambridge University Press.

Hsiao, C. (2003). *Analysis of panel data.* (2nd ed.). Cambridge University Press.

Hubbard, G. (1998). Capital-market imperfections and investment. *Journal of Economic Literature*, *36*(1), 193–225.

ILO. (1993). The revised international standard classification of occupation. International Labour Office Bureau of Statistics ,Geneva.

International Study Group on Exports and Productivity (ISGEP). (2008). Understanding cross-Country differences in exporter premia: Comparable evidence for 14 Countries. *Review of World Economics*, *144*(4), 596–635.

Isard, W. (1960). *Methods of regional analysis: An introduction to regional science.* 1st edition. Cambridge, New York: MIT and Wiley.

Isserman, A. M. (1977). The location quotient approach to estimating regional economic impacts. *Journal of the American Institute of Planners*, *43*(1), 33–41.

Iwaisako, T., & Futagami, K. (2013). Patent protection, capital accumulation, and economic growth. *Economic Theory*, *52*(2), 631–668.

Jaffe, A., Trajtenberg, M., & Henderson, R. (1993). Geographic localization of knowledge spillovers as evidenced by patent citations. *The Quarterly Journal of Economics*, *108*(3), 577–598.

Jaumandreu, J.(2003). *Does innovation spur employment? A firm-level analysis using Spanish CIS data.* Retrieved from http://www.eco.uc3m.es/temp/ jaumandreu.pdf

Jefferson, G., Huamao, B., Xiaojing, G., & Xiaoyun, Y. (2006). R&D Performance in Chinese industry. *Economics of Innovation and New Technology*, *15*(4-5), 345–366.

Jones, C. (1995). R&D-based models of economic growth. *Journal of Political Economy*, *103*(4), 759–784.

Jones, C. (1995). Time series tests of endogenous growth models. *The Quarterly Journal of Economics*, *110*(2), 495–525.

Jorgenson, D. (2001). Information technology and the U.S. economy. *American Economic Review*, *91*(1), 1–32.

Jorgenson, D., & Fraumeni, M. (1989). The accumulation of human capital and nonhuman capital. In E. Lipsey & H. Tice (Eds.), *The measurement of saving, investment and wealth* (pp. 1948–1984). University of Chicago Press.

Jovanovic, B., & Nyarko, Y. (1996). Learning by doing and the choice of technology. *Econometrica*, *64*(6), 1299–1310.

Katsoulacos, Y. (1986). *The employment effect of technical change: A theoretical study of new technology and the labor market.* (1st ed.). Wheatsheaf.

Khan, B. Z. (2005). *The Democratization of Invention: Patents and Copyrights in American Economic Development, 1790-1920* (NBER Books). National Bu-

reau of Economic Research, Inc. Retrieved from http://ideas.repec.org/b/nbr/nberbk/khan05-1.html

Kim, H., & Park, Y. (2008). The impact of R&D collaboration on innovative performance in Korea: A Bayesian network approach. *Scientometrics*, *75*(3), 535–554.

Koo, J. (2005). How to analyze the regional economy with occupation data. *Economic Development Quarterly*, *19*(4), 356–372.

Krugman, P. R. (1997). *The age of diminished expectations: U.S. economic policy in the 1990s*. (3rd ed.). MIT Press.

Kuznets, S. (1940). Schumpeters's business cycles. *The American Economic Review*, *30*(2), 257–271.

Kydland, F., & Prescott, E. (1982). Time to Build and Aggregate Fluctuations. *Econometrica*, *50*(6), 1345–70.

Lachenmaier, S., & Rottmann, H. (2011). Effects of innovation on employment: A dynamic panel analysis. *International Journal of Industrial Organization*, *29*(2), 210–220.

Lengyel, B., & Ságvári, B. (2011). Creative occupations and regional development in Hungary: Mobility of talent in a one-centered transition economy. *European Planning Studies*, *19*(12), 2073–2093.

Leonard-Barton, D. (1992). Core capabilities and core rigidities: A paradox in managing new product development. *Strategic Management Journal*, *13*(S1), 111–125.

Leontief, W. (1941). *The structure of the American economy*.

Lerner, A. (1953). On the marginal product of capital and the marginal efficiency of investment. *Journal of Political Economy*, *61*(1), 1–14.

Lööf, H., & Heshmati, A. (2002). Knowledge capital and performance heterogeneity: A firm-level innovation study. *International Journal of Production Economics*, *76*(1), 61–85.

Lucas, R. (1967). Adjustment costs and the theory of supply. *Journal of Political Economy*, *75*(4), 321–334.

Lucas, R. (1967). Optimal investment policy and the flexible accelerator. *International Economic Review*, *8*(1), 78–85.

Lucas, R. (1988). On the mechanics of economic development. *Journal of Monetary Economics*, *22*(1), 3–42.

Maddison, A. (1982). *Phases of capitalist development*. (1st ed.). Oxford University Press.

Mairesse, J., & Jaumandreu, J. (2005). Panel-data estimates of the production function and the revenue function: What difference does it make?*. *Scandinavian Journal of Economics*, *107*(4), 651–672.

Mairesse, J., & Mohnen, P. (2005). The importance of R&D for innovation: A reassessment using French survey data. In A. Link & F. Scherer (Eds.), *Essays in Honor of Edwin Mansfield* (pp. 129–143). Springer US.

Malerba, F., & Orsenigo, L. (1993). Technological regimes and firm behavior. *Industrial and Corporate Change*, *2*(1), 45–71.

Malerba, F., & Orsenigo, L. (1995). Schumpeterian patterns of innovation. *Cambridge Journal of Economics*, *19*(1), 47–65.

Malthus, T. R. (1798). *Essay on the principle of population.* (1st ed.). J. Johnson, London.

Mankiw, G., Romer, D., & Weil, D. (1992). A Contribution to the empirics of economic growth. *The Quarterly Journal of Economics*, *107*(2), 407–437.

Mansfield, E. (1961). Technical change and the rate of imitation. *Econometrica: Journal of the Econometric Society*, 741–766.

Markusen, A. (2004). Targeting occupations in regional and community economic development. *Journal of the American Planning Association*, *70*(3), 253–268.

Markusen, A. (2006). Urban development and the politics of a creative class: Evidence from a study of artists. *Environment and Planning A*, *38*(10), 1921–1940.

Markusen, A., Wassall, G. ., DeNatale, D., & Cohen, R. (2008). Defining the creative economy: Industry and occupational approaches. *Economic Development Quarterly*, *22*(1), 24–45.

Marlet, G., & Woerkens, C. (2004). *Skills and creativity in a cross-section of Dutch cities* (Working Paper, no 04-29). Utrecht School of Economics.

Mason,G., Bishop,K., & Robinson,G. (2009). Business growth and innovation: The wider impact of rapidly growing firms in UK city-regions.

Mathur, V. (1999). Human capital-based strategy for regional economic development. *Economic Development Quarterly*, *13*(3), 203–216.

Mellander, C., & Florida, R. (2007). *The creative class or human capital? Explaining regional development in Sweden* (CESIS-Centre of Excellence for Science and Innovation Studies No. 79). Royal Institute of Technology, CESIS - Centre of Excellence for Science and Innovation Studies.

Mellander, C., & Florida, R. (2011). Creativity, talent, and regional wages in Sweden. *The Annals of Regional Science*, *46*(3), 637–660.

Meyer, P. (2005). Preliminary estimates of multifactor productivity growth, *128*(6), 32–43.

Miguel- Benavente, J. (2006). The role of research and innovation in promoting productivity in Chile. *Economics of Innovation and New Technology*, *15*(4-5), 301–315.

Mincer, J. (1958). Investment in human capital and personal income distribution. *The Journal of Political Economy*, *66*(4), 281–302.

Mincer, J. A. (1974). *Schooling, Experience, and Earnings* (NBER Books). National Bureau of Economic Research, Inc. Retrieved from http:// econpapers.repec.org/bookchap/nbrnberbk/minc74-1.htm

Möller, J., & Tubadji, A. (2009). The creative class, bohemians and local labor market performance: A micro-data panel study for Germany 1975–2004. *Journal of Economics and Statistics*, *229*(2-3), 270–291.

Musso, P., & Schiavo, S. (2008). The impact of financial constraints on firm survival and growth. *Journal of Evolutionary Economics*, *18*(2), 135–149.

Myrdal, G. (1957). *Economic theory and under-developed regions*. (1st ed.). Harper Torchbooks.

Negassi, S. (2004). R&D co-operation and innovation a microeconometric study on French firms. *Research Policy*, *33*(3), 365–384.

Nelson, R., & Winter, S. (1993). In search of useful theory of innovation. *Research Policy*, *22*(2), 108–108.

Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica*, *49*(6), 1417–26.

Nickell, S. (1999). Product markets and labor markets. *Labor Economics*, *6*(1), 1–20.

Nickell, S., & Komg, P. (1989). *Technical progress and jobs* (Paper No. 366). London School of Economics - Centre for Labor Economics.

Nonaka, I., & Takeuchi, H. (1995). *The knowledge-creating company: How Japanese companies create the dynamics of innovation*. New York: Oxford University Press.

North, D. (1992). Institutions, ideology, and economic performance. *Cato Journal*, *11*(3), 477–496.

OECD. (1995). The measurement of scientific and technological activities: Manual on the measurement of human resources devoted to S&T"Canberra Manual."

OECD. (2002). Frascati manual: Proposed standard practice for surveys on research and experimental development. Organization for Economic Co-operation and Development.

OECD. (2005). *Oslo Manual: Guidelines for collecting and interpreting innovation data* (3rd ed.). Paris: Organization for Economic Co-operation and Development.

OECD. (2008). Compendium of patent statistics. Organization for Economic Co-operation and Development.

OECD. (2009). *Innovation in science, technology and industry: OECD patent statistics manual.* Retrieved from www.oecd.org/.../oecdpatentstatisticsmanual.htm

OECD. (2013). Main science and technology indicators. Retrieved November 28, 2013, from http://www.oecd.org/science/inno/msti.htm

Okamuro, H. (2007). Determinants of successful R&D cooperation in Japanese small businesses: The impact of organizational and contractual characteristics. *Research Policy*, *36*(10), 1529–1544.

Okamuro, H., Kato, M., & Honjo, Y. (2011). Determinants of R&D cooperation in Japanese start-ups. *Research Policy*, *40*(5), 728–738.

Parker, C. (2009). *The economics of entrepreneurship.* (1st ed.). Cambridge University Press.

Parker, C. (2013). Theories of entrepreneurship, innovation and the business cycle. In *Innovation, Entrepreneurship, geography and growth* (pp. 5–24). Blckwell Publishing Ltd.

Peck, J. (2005). Struggling with the creative class. *International Journal of Urban and Regional Research*, *29*(4), 740–770.

Pellandra, A. (2013). *Firms'exporting, employment and wages: Evidence from Chile.* Retrieved from www.iza.org/conference.../pellandra_a8726.pdf

Peters, B. (2008). *Innovation and firm performance: An empirical investigation for German firms.* (1st ed.). Heidelberg; New York: Physica-Verlag.

Peters, B. (2009). Persistence of innovation: Stylised facts and panel data evidence. *The Journal of Technology Transfer*, *34*(2), 226–243.

Peters, B., & Rammer, C. (2013). Innovation panel surveys in Germany. In F. Gault (Ed.), *Handbook of the economics of innovation and technological change* (pp. 135–177). Edward Elgar Publishing.

Phelps, E. (1966). Models of technical progress and the golden rule of research. *The Review of Economic Studies*, *33*(2), 133–145.

Piva, M., & Vivarelli, M. (2005). Innovation and employment: Evidence from Italian microdata. *Journal of Economics*, *86*(1), 65–83.

Plessis, M. (2007). The role of knowledge management in innovation. *Journal of Knowledge Management*, *11*(4), 20–29.

Polèse, M. (2012). The arts and local economic development: Can a strong arts presence uplift local economies? A study of 135 Canadian cities. *Urban Studies*, *49*(8), 1811–1835.

Porter, M. (1998). *The competitive advantage of nations*. London: Macmillan Business.

Porter, M. (2008). *On competition*. Boston, MA: Harvard Business School Pub.

Qian, H. (2013). Diversity versus tolerance: The social drivers of innovation and entrepreneurship in US Cities. *Urban Studies*, *50*(13), 2718–2735.

Reenen, J. V. (1997). Employment and Technological Innovation: Evidence from U.K. Manufacturing Firms. *Journal of Labor Economics*, *15*(2), 255–284.

Roessner, D., Porter, A., Newman, N., & Jin, X. (2002). A comparison of recent assessments of the high-tech competitiveness of nations. *International Journal of Technology Management*, *23*(6), 536–557.

Romer, P. (1986). Increasing returns and long-run growth. *Journal of Political Economy*, *94*(5), 1002–1037.

Romer, P. (1990). Endogenous technological change. *Journal of Political Economy*, *98*(5), S71–S102.

Roodman, D. (2009). A note on the theme of too many instruments. *Oxford Bulletin of Economics and Statistics*, *71*(1), 135–158.

Roodman, D. (2009). How to do xtabond2: An introduction to difference and system GMM in Stata. *Stata Journal*, *9*(1), 86–136.

Rosen, S. (1972). Learning and experience in the labor market. *The Journal of Human Resources*, *7*(3), 326–342.

Rottman, H., & Ruschinski, M. (1998). The labor demand and the innovation behavior of firms: An empirical investigation for West German manufacturing firms.

Sacchetti, F., Sacchetti, S., & Sugden, R. (2009). Creativity and socioeconomic development: Space for the interests of publics. *International Review of Applied Economics*, *23*(6), 653–672.

Sacchetti, S., & Tortia, E. (2013). Satisfaction with creativity: A study of organizational characteristics and idividual motivation. *Journal of Happiness Studies*, *14*(6), 1789–1811.

Schmalensee, R. (1992). Sunk costs and market structure: A review article. *The Journal of Industrial Economics*, *40*(2), 125–134.

Schmidt, T., & Rammer, C. (2007). *Non-technological and technological innovation: Strange bedfellows?* (ZEW Discussion Paper No. 07-052). ZEW - Zentrum für Europäische Wirtschaftsforschung / Center for European Economic Research.

Schultz, T. (1962). Reflections on investment in man. *Journal of Political Economy*, *70*(5), 1–8.

Schultz, T. (1963). *Economic value of education*. (1st ed.). Columbia University Press.

Schultz, T. (1989). Investing in people: Schooling in low income countries. *Economics of Education Review*, *8*(3), 219–223.

Schumpeter, J. (1927). The explanation of the business cycle. *Economica*, (21), 286. doi:10.2307/2548401

Schumpeter, J. (1934). *The theory of economic development: An inquiry into profits, capital, credit, interest, and the business cycle*. Cambridge University Press, 1st edition.

Schumpeter, J. A. (1939). *Business cycles: A theoretical, historical, and statistical analysis of the capitalist process*. Martino Pub.

Scott, A. (2006). Creative Cities: Conceptual issues and policy questions. *Journal of Urban Affairs*, *28*(1), 1–17.

Scott, A., & Storper, M. (1992). *Pathways to Industrialization and Regional Development*. Routledge.

Segarra-Blasco, A. (2010). Innovation and productivity in manufacturing and service firms in Catalonia: A regional approach. *Economics of Innovation and New Technology*, *19*(3), 233–258.

Sen, A. (2002). *Rationality and freedom*. (1st ed.). Belknap Press.

Shalley, C. E. (1995). Effects of coaction,expected evaluation and goal setting on creativity and productivity. *Academy of Management Journal*, *38*(2), 483–503.

Shell, K. (1967). *Essays on the theory of optimal economic growth*. MIT Press, 1st edition.

Siggelkow, N. (2003). Why Focus? A Study of intra-industry focus effects, *51*(2), 121–151.

Skinner, J., & Staiger, D. (2005). *Technology adoption from hybrid corn to beta blockers*. NBER, no 11251.

Smith, A. (1776). *An inquiry into the nature and causes of the wealth of Nations*. Oxford: Clarendon Press.

Smolny, W. (1998). Innovations, prices and employment: A theoretical model and an empirical application for West German manufacturing firms. *The Journal of Industrial Economics*, *46*(3), 359–381.

Solow, R. (1956). A contribution to the theory of economic growth, *70*(1), 65–94.

Solow, R. (1957). Technical change and the aggregate production function. *The Review of Economics and Statistics*, *39*(3), 312–320.

Solow, R. (1957b). Technical Change and the Aggregate Production Function. *The Review of Economics and Statistics*, *39*(3), 312. doi:10.2307/1926047

Stiglitz, J. (1975). The theory of screening, education, and the distribution of income. *The American Economic Review*, *65*(3), 283–300.

Stolarick, K., & Florida, R. (2006). Creativity, connections and innovation: a study of linkages in the Montréal Region. *Environment and Planning A*, *38*(10), 1799–1817.

Stone, A., Rose, S., Lal, B., & Shipp, S. (2008). *Measuring innovation and intangibles: A business perspective* (IDA document No. D-3704). Science and Technology Policy Institute.

Stoneman, P. (1983). *The economic analysis of technological change*. Oxford, New York: Oxford University Press.

Strumsky, D., Lobo, J., & van der Leeuw, S. (2012). Using patent technology codes to study technological change. *Economics of Innovation and New Technology*, *21*(3), 267–286.

Stuetzer, M., Obschonka, M., Brixy, U., Sternberg, R., & Cantner, U. (2014). Regional characteristics, opportunity perception and entrepreneurial activities. *Small Business Economics*, *42*(2), 221–244.

Sutton, J. (1991). *Sunk costs and market structure: Price competition, advertising, and the evolution of concentration*. MIT Press.

Szczygielski, K., Grabowski, W., & Woodward, R. (2013). *Innovation and the growth of service firms: The Polish case* (No. 0453). CASE-Center for Social and Economic Research.

Tether, B. (1998). Small and large firms: sources of unequal innovations? *Research Policy*, *27*(7), 725–745.

Theodore, N., & Carlson, V. (1998). Targeting job opportunities: Developing measures of local employment. *Economic Development Quarterly*, *12*(2), 137–149.

Thompson, M., & Rushing, F. (1999). An empirical analysis of the impact of patent protection on economic growth : An extension, *21*(1), 61–79.

Thompson, W., & Thompson, P. (1985). From industries to occupations: rethinking local economic development. *Economic Development Commentary.*, *9*(3).

Tidd, J., Bessant, J., & Pavitt, K. (2001). *Managing innovation: Integrating technological, market and organizational change.* Chichester [England]; New York: John Wiley.

Tiffen, M. (1995). Population density, economic growth and societies in transition: Boserup reconsidered in a Kenyan case-study. *Development and Change*, *26*(1), 31–66.

Tiruneh, E. A. (2014). Regional Economic Development in Italy: Applying the Creative Class Thesis to a Test. *Journal of the Knowledge Economy*, *5*(1), 19–36. doi:10.1007/s13132-012-0126-3

Tödtling, F., & Trippl, M. (2005). One size fits all? Towards a differentiated regional innovation policy approach. *Research Policy*, *34*(8), 1203–1219.

Treadway, A. (1971). The rational multivariate flexible accelerator. *Econometrica*, *39*(5), 845–855.

Tripsas, M. (1997). Unraveling the process of creative destruction: Complementary assets and incumbent survival in the typesetter industry. *Strategic Management Journal*, *18*(s 1), 119–142.

Trufat, B. (2006). Efficiency of representative democracy: A comparative study of two competing models. In A. Ott & R. Cebula (Eds.), *The Elgar Companion to Public Economics: Empirical Public Economics* (pp. :343–364).

Utterback, J. (1994). *Mastering the dynamics of innovation: How companies can seize opportunities in the face of technological change.* Boston (Mass.): Harvard Business School Press.

Uzawa, H. (1965). Optimum technical change in an aggregative model of economic growth. *International Economic Review*, *6*(1), 18.

Van Leeuwen, G., & Klomp, L. (2006). On the contribution of innovation to multi-factor productivity growth. *Economics of Innovation and New Technology*, *15*(4-5), 367–390.

Vernon, R. (1966). International investment and international trade in the product cycle. *The Quarterly Journal of Economics*, 190–207.

Vom Berge, ., König, M., & Seth, S. (2013). *Sample of integrated labor market biographies (SIAB) 1975-2010*. FDZ Datenreport. Documentation on Labour Market Data.

Wade, R. (2005). Failing states and cumulative causation in the world system. *International Political Science Review / Revue Internationale de Science Politique*, *26*(1), 17–36.

Wagner, J. (2012). International trade and firm performance: a survey of empirical studies since 2006. *Review of World Economics*, *148*(2), 235–267.

Weil, D. (2009). *Economic growth* (Vol. 2nd edition). Boston: Pearson Addison Wesley.

Windmeijer, F. (2005). A finite sample correction for the variance of linear efficient two-step GMM estimators. *Journal of Econometrics*, *126*(1), 25–51.

Wooldridge, J. M. (2010). *Econometric analysis of cross-section and panel data*. (2nd ed.). Cambridge, Massa.

Wragg, R., & Robertson, J. (1978). *Post-war trends in employment, productivity, output, labour costs, and prices by industry in the United Kingdom*. Dept. of Employment.

Yang, C., & Huang, C. (2005). R&D, Size and Firm Growth in Taiwan's Electronics Industry. *Small Business Economics*, *25*(5), 477–487.

Young, A. (1991). Learning by doing and the dynamic effects of international trade. *The Quarterly Journal of Economics*, *106*(2), 369–405.

Young, A. (1993). Invention and bounded learning by doing. *Journal of Political Economy*, *101*(3), 443–472.

ZEW. (2013). *Innovation in Germany: Survey of CIS 2003-2010*. Center for European Economic Research, Mannheim, Germany.

Zimmermann, K. (1991). The employment consequences of technological advance, demand and labor costs in 16 German industries. *Empirical Economics*, *16*(2), 253–266.

Zucker, L., Darby, M., & Brewer, M. (1998). Intellectual human capital and the birth of U.S. biotechnology enterprises. *The American Economic Review*, *88*(1), 290–306.

Appendices

Appendix A
Additional data and estimation results for Essay I

Appendix A1
Creative class and art experts identification using IAB database, Germany

Occupational category	IAB occupation code
Creative core	
Engineers	601: Engineers of machine, vehicle & construction 602: Electrical engineers 603 Architects 604: Surveyors 605: Mining, metallurgical and foundry engineers 606: Other Manufacturing Engineers 607: Other engineers 611: Chemists, chemical engineers 612: Physicists, physics engineers, mathematicians 52: Gardening Architects
Scientists, think tank researchers	881: Social scientists and statisticians 883:Other scientists
Professors and faculty members	871: University professors, faculty members and lecturers at higher vocational schools and academies
Analysts, entrepreneurs, leading administrators	751: Entrepreneurs, CEO
Head of business unit	752: Management Consultant, organizers 762: Senior administrative and decisive
Opinion makers: dispersed in other categories	774: Software programmers / engineers, data processing professionals

Occupational category	IAB occupation code
Creative professionals	
High-tech services sectors and technicians	621: Mechanical Engineers 622:Electric technicians 623: General technicians 624: Surveyors 625: Mining, metallurgical, foundry technicians 626: Chemical engineers, physical science 627: Other manufacturing technicians 628 :Other technicians 629: Foreman, foreman 631: Biological and special technical professionals 632: Physical and mathematical and technical 633: Chemical laboratory 634: Photo lab technicians 635 :Draftsmen
Financial services	691: Bankers 753: Auditors and tax advisers
Legal services	813: legal services and legal consultants
Business services	703: Business consultancy experts 822: Business analysts
Humanities	882: Humanity experts
Art experts (Bohemians)	
Creative writers and performing artists	821: Publicity workers, promoters and advertisers 823: Librarians, archivists, museum professionals 831: Musicians 832: Performing Artists 833: Artistic graphic makers
Photographers, image and sound recording equipment operators, and other fashion models	837: Photographers 835: Artistic and associated professions of stage, screen and sound
Artistic, entertainment and sports associate professionals	838: artists, professional athletes, artistic paramedics

Appendix A2
AR (3) and AR (2) process of regional GDP, employment and wage growth

Varia-ble	Lags	Creative class				Human capital			
	Lags	AR	OLS	FE	SGMM	AR	OLS	FE	SGMM
Gross domestic product growth	L1. gdp	.563 (32.65)***	.925 (53.05)***	.333 (22.07)***	.814 (20.05)***	.563 (32.65)***	.914 (52.35)***	.334 (22.03)***	.863 (28.99)***
	L2. gdp	.113 (6.14)***	.100 (4.31)***	.029 (1.83)*	.119 (3.59)***	.113 (6.14)***	.098 (4.22)***	.028 (1.75)*	.124 (3.90)***
	L3. gdp	.320 (18.92)***	-.044 (-2.70)***	-.027 (-2.18)**	-.048 (-1.73)*	.320 (18.92)***	-.036 (-2.23)**	-.027 (-2.17)**	-.050 (2.50)**
	Sum β	0.996	0.981	0.335	0.885	0.996	0.976	0.335	0.937
	Obs.	3152	3152	3152	3152	3152	3152	3152	3152
Employment growth	L1. emp	1.028 (66.27)***	.923 (59.38)***	.361 (27.82)***	1.102 (31.36)***	1.028 (66.27)***	.924 (59.57)***	.382 (29.07)***	.881 (24.08)***
	L2. emp	-.031 (-2.05)**	.022 (1.47)	.024 (2.19)**	-.191 (-3.42)***	-.031 (-2.05)**	.025 (1.71)*	.025 (2.25)**	.055 (1.49)
	Sum β	0.997	0.945	0.385	0.911	0.997	0.949	0.407	0.936
	Obs.	3546	3546	3546	3152	3546	3546	3546	3546
Wage growth	L1. wage	.754 (46.50)***	.689 (42.67)***	.423 (24.32)***	.673 (22.32)***	.754 (46.50)***	.692 (42.89)***	.426 (24.56)***	.685 (21.91)***
	L2. wage	.238 (14.63)*	.260 (16.06)***	.085 (4.83)**	.245 (-9.66)***	.238 (4.63)***	.262 (16.17)***	.091 (5.15)**	.242 (8.81)***
	Sum β	0.992	0.949	0.508	0.918	0.992	0.954	0.517	0.927
	Obs.	3546	3546	3546	3152	3546	3546	3546	3546
	Re-gions	394	394	394	394	394	394	394	394

*p<0.1, **p<0.05, ***p<0.01, t-statistic in brackets

Appendix A3
AR (2) process of regional other creative class growth

Variable	Share of other creative class			
SCP	AR	OLS	FE	One-step SGMM
L1.Share of other creative class	1.036 (66.15)***	.916 (78.87)***	.422 (32.21)***	.644 (7.51)***
L2.Share of other creative class	-.047 (-3.00)***	-.013 (-1.24)	-.015 (-1.83)*	-.010 (-0.60)
Sum ß	0.989	0.903	0.409	0.654
Obs.	3546	3546	3546	3546
Regions	394	394	394	394

*p<0.1, ***p<0.01, t-statistic in brackets

Appendix B
Additional data and estimation results for Essay II

Appendix B1
Corporate membership status by year

Year	Member	Non-member	Total
2003	361	960	1321
2004	397	850	1247
2005	519	1121	1640
2006	581	1224	1805
2007	562	1231	1793
2008	605	1293	1898
2009	509	999	1508
2010	452	1081	1533
Total	3986	8759	12745

Appendix B2
Corporate membership status by industry and year

Year	Manufacturing			Services		
	Member	Non-member	Total	Member	Non-member	Total
2003	247	515	762	114	445	559
2004	276	455	731	121	395	516
2005	353	663	1016	166	458	624
2006	417	694	1111	164	530	694
2007	380	722	1102	182	509	691
2008	426	782	1208	179	511	690
2009	347	615	962	162	384	546
2010	317	652	969	135	429	564
Total	2763	5098	7861	1223	3661	4884

Appendix B3
Export status by year

Year	Exporter	Non-exporter	Total
2003	685	636	1321
2004	574	673	1247
2005	791	849	1640
2006	901	904	1805
2007	870	923	1793
2008	835	1063	1898
2009	720	788	1508
2010	692	841	1533
Total	6068	6677	12745

Appendix B4
Export status by industry and year

Year	Manufacturing			Services		
	Exporter	Non-exporter	Total	Exporter	Non-exporter	Total
2003	254	508	762	431	128	559
2004	211	520	731	363	153	516
2005	325	691	1016	466	158	624
2006	379	732	1111	522	172	694
2007	378	724	1102	492	199	691
2008	353	855	1208	482	208	690
2009	326	636	962	394	152	546
2010	291	678	969	401	163	564
Total	2517	5344	7861	3551	1333	4884

Appendix B5
Description and measurement of firm performance and innovation input indicators

Variable	Description	Measurement
L1.EMP	Fist lag of employment	Employment in log
L1.SAL	First lag of sale	Sales turnover in log
L1.PROD	First lag of labor productivity	Output per employee in log
L1.FUES	First lag of share of R&D expenditure	R&D expenditure per output
FUES	Share of (current) R&D expenditure	R&D expenditure per output
L1.INVS	First lag of share of investment innovation expenditure	Investment innovation expenditure per output
INVS	Share of (current) investment innovation expenditure	Investment innovation expenditure per output
L1.IAS	First lag of share of (current) total innovation expenditure	Total innovation expenditure per output
IAS	Share of (current) total innovation expenditure	Total innovation expenditure per output
EXP	Exporting status	1 if a firm exports otherwise 0
MEM	Membership to corporate group	1 if a firm is part of corporate group else 0

Appendix B6
AR (1): process of employment, sales and wage growth using innovation input

Lagged dependent variable	Manufacturing				Services			
	AR	OLS	FE	two-step SGMM	AR	OLS	FE	two-step SGMM
L1.EMP	.984 (423.37)***	.978 (346.35)***	.414 (21.49)***	.883 (58.14)***	.975 (210.29)***	.926 (125.32)***	.143 (6.11)***	.781 (37.57)***
L1.SAL	.984 (311.67)***	.974 (248.46)***	.118 (5.91)***	.725 (27.69)***	.972 (195.87)***	.967 (175.10)***	.077 (2.73)***	.660 (49.92)***
L1.PROD	.912 (130.64)***	.900 (123.05)***	-.072(-3.51)***	.368 (14.96)***	.922 (114.54)***	.917 (109.46)***	-.004 (-0.19)	.426 (27.67)***
Obs.	4175	4175	4175	4175	2472	2472	2472	2472
Firms	--	--	1802	1802	---	---	1099	1099

***p<0.01, z-statistic in parentheses

Appendix B7
Description and measurement of firm performance and innovation output indicators

Variable	Description	Measurement
L1.EMP	First lag of employment	Employment in log
L1.SAL	Fist lag of sales	Sales turnover in log
L1.PROD	First lag of labor productivity	Output per employee in log
L1.FPD	First lag of product innovation to firm	1 if product innovation is introduced to firm 0 otherwise
FPD	Current product innovation to firm	1 if product innovation is introduced to firm 0 otherwise
L1.MPD	Fist lag of product innovation to market	1 if product innovation is introduced to market 0 otherwise
MPD	Current product innovation to market	1 if product innovation is introduced to market 0 otherwise
L1.REK	Fist lag of process innovation or cost reduction innovation	1 if process innovation or cost reduction innovation is produced 0 otherwise
REK	Current process innovation	1 if process innovation or cost reduction innovation is produced 0 otherwise
EXP	Exporting status	1 if a firm exports 0 else
MEM	Corporate membership status	1 if part of corporate group 0 else

Appendix B8

*AR (1): process of employment, sales and wage growth using innovation output*

Lagged dependent variable	Manufacturing				Services			
	AR	OLS	FE	two-step SGMM	AR	OLS	FE	two-step SGMM
L1.EMP	.984 (433.37)***	.976 (344.50)***	.412 (21.46)***	.933 (61.95)***	.975 (210.29)***	.970 (191.81)***	.141 (6.02)***	.903 (56.50)***
L1.SAL	.984 (311.67)***	.972 (253.97)***	.091 (4.53)***	.768 (22.78)***	.972 (195.87)***	.967 (176.18)***	.074 (2.63)***	.783 (25.00)***
L1.PROD	.912 (130.64)***	.899 (123.42)***	-0.076((-3.69)***	.494 (19.28)***	.922 (114.54)***	.919 (110.94)***	-.004((- 0.19)	.726 (28.17)***
Obs.	4175	4175	4175	4175	2472	2472	2472	2472
Firms	---	---	1802	1802	---	---	1099	1099

***$p<0.01$, z-statistic in parentheses

Appendix C
Additional data and estimation results for Essay III

Appendix C1
Planning regions in Germany

Appendix C2
Regional economic performance and technological innovation indicators
(Obs. =480)

Variable	Mean	Std. Dev.	Min	Max
Ln per capita income	4.094	.894	1.993	7.147
Ln employment	12.300	.690	10.527	14.101
Ln wage	4.443	.110	4.17	4.748
Ln patents applied	4.766	1.326	.182	7.280
Ln population density	13.440	.649	11.529	15.226

Appendix C3
Log of per capita income over five years
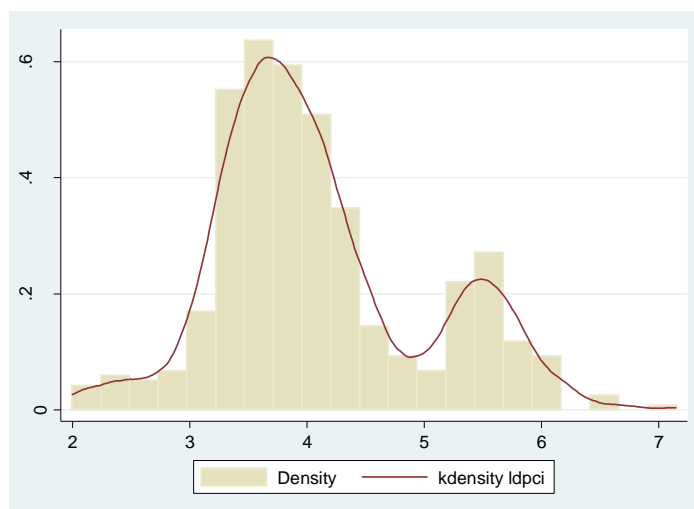
Appendix C4
Log of per capita income in each year

Graphs by consecutive year
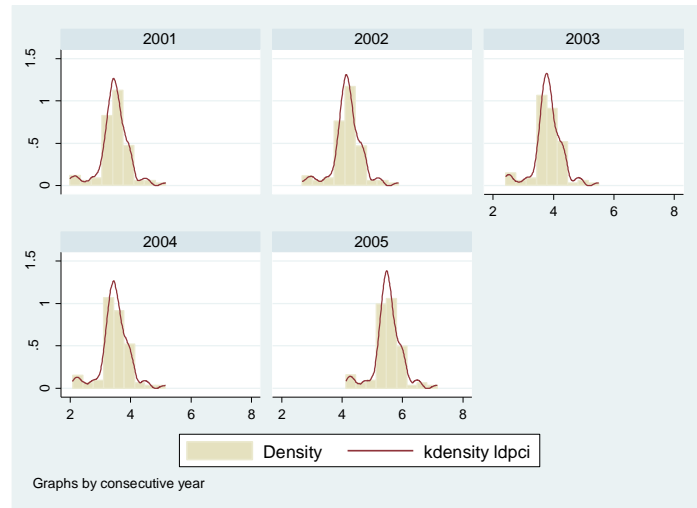
Appendix C5
Log of employment over five years
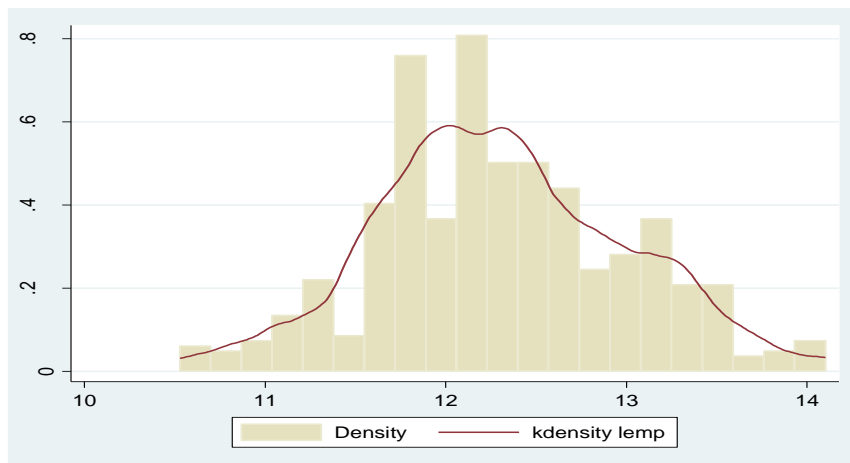
Appendix C6
Log of employment in each year

Graphs by consecutive year
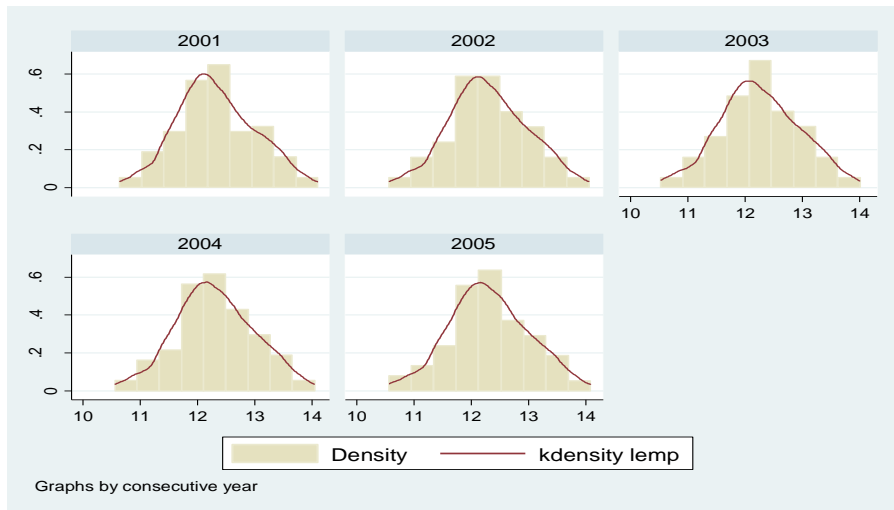
Appendix C7
Log of median wage over five years
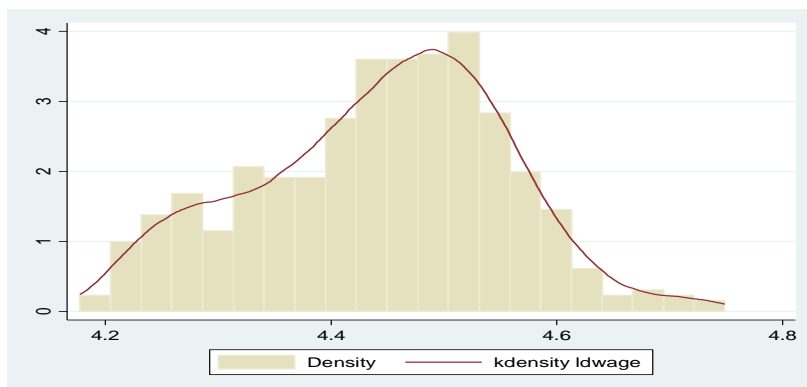
Appendix C8
Log of median wage in each year
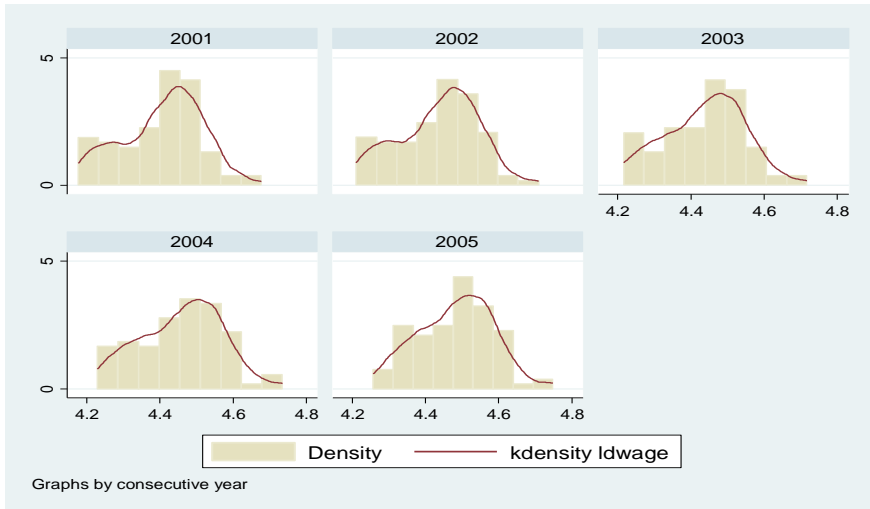
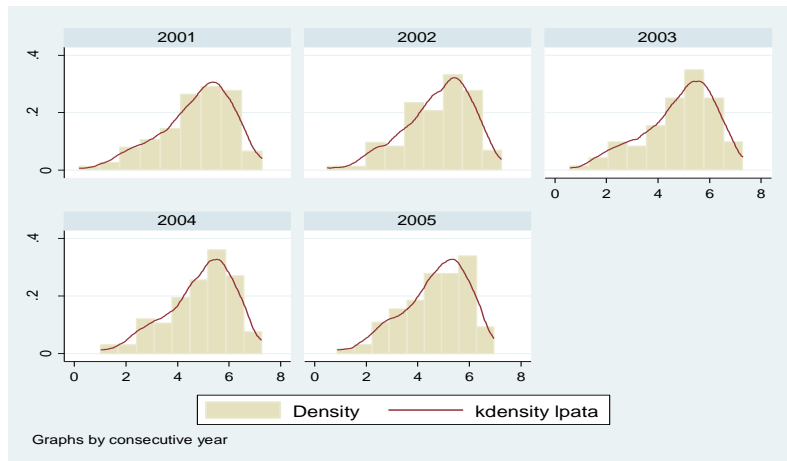## *Appendix C9*
Share of R&D expenditure over five years
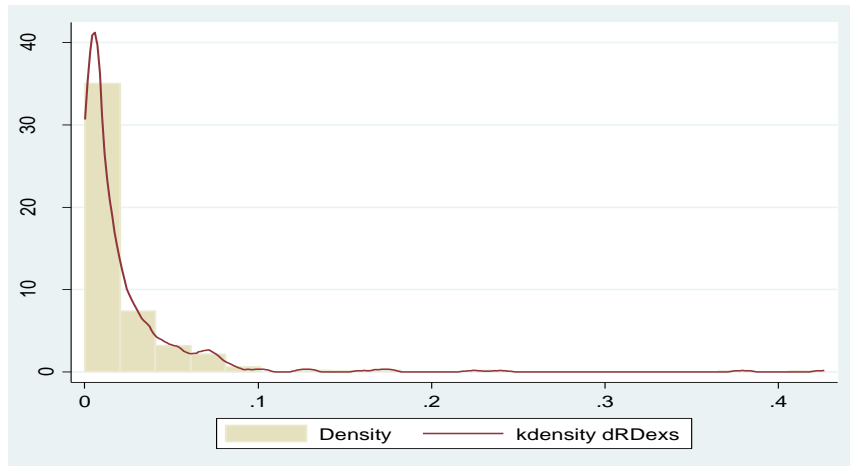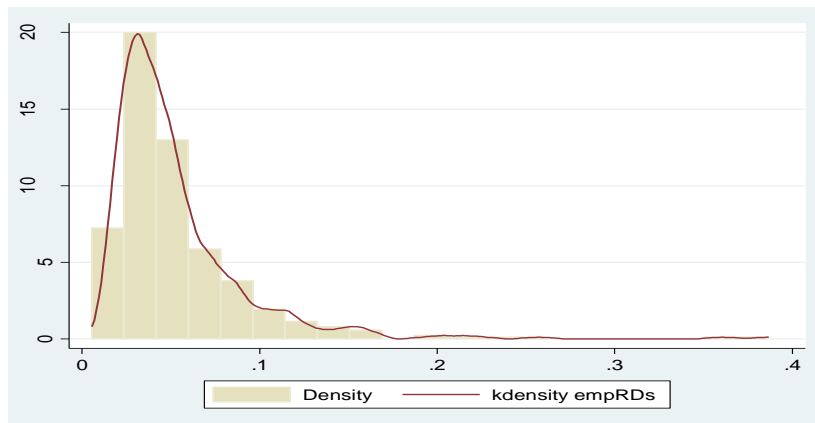
Appendix C10
Share of R&D expenditure in each year

Graphs by consecutive year
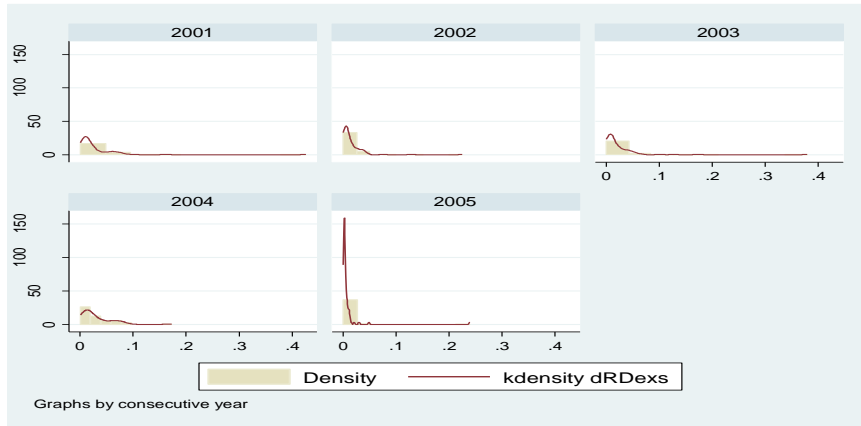
Appendix C11
Log of patents applied per 100,000 people over five years
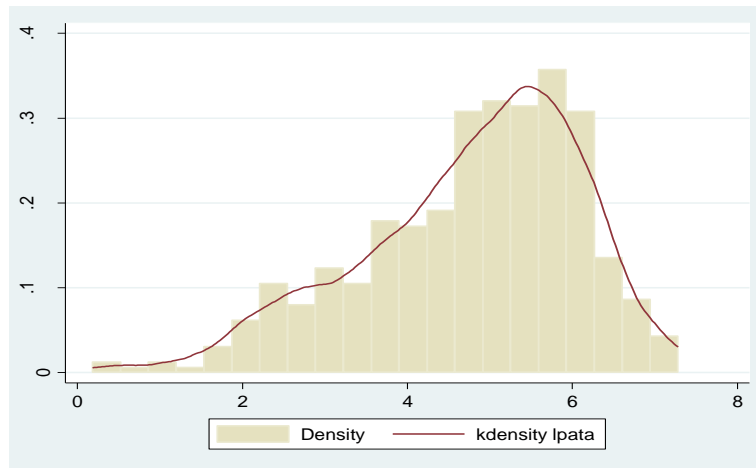
Appendix C12
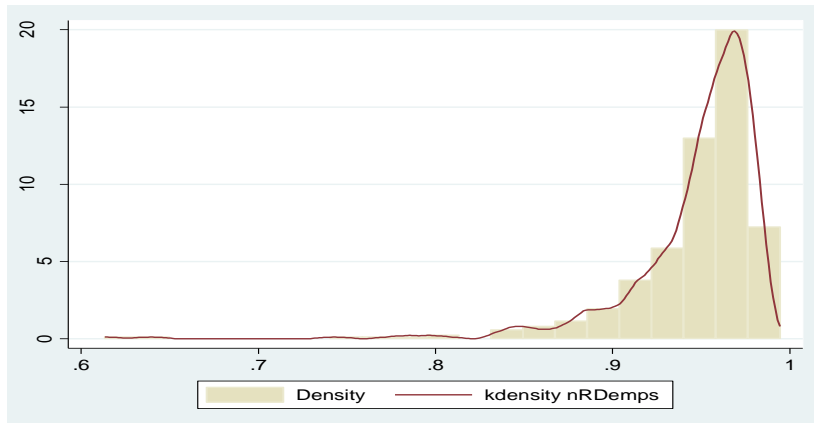### *Log of patents applied per 100,000 people in each year*

Graphs by consecutive year

Appendix C13
Share of researchers over five years

Appendix C14
Share of researchers in each year

Graphs by consecutive year
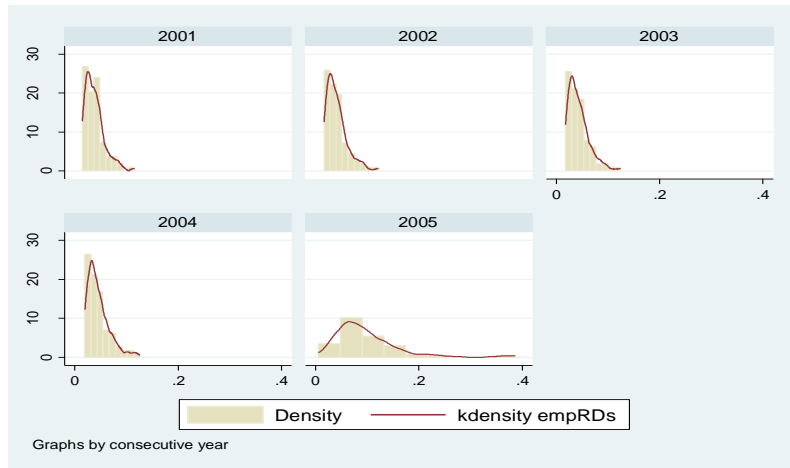
Appendix C15
Share of non-researchers over five years

Appendix C16
Share of non-researchers in each year

Graphs by consecutive year
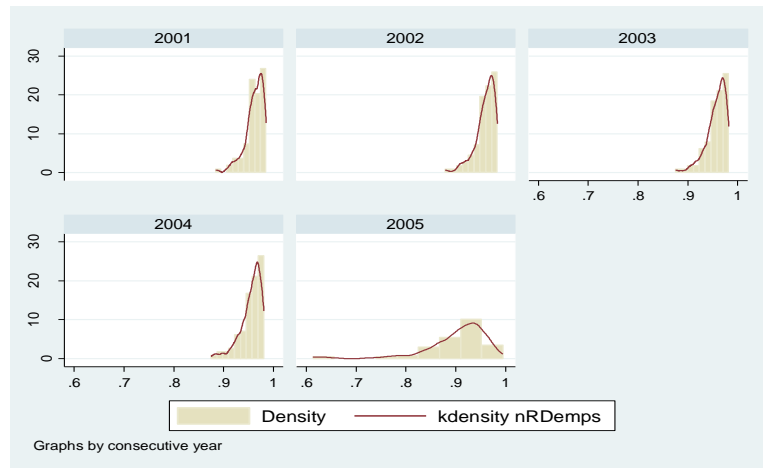
Appendix C17
AR (1) process of regional per capita income, employment and wage growth

Lags of dependent variables	AR	OLS	FE	two-step SGMM
Lag1 per capita income	.2629 (.0814)***	.9849 (.0061)***	.1250 (.0537)**	.9340 (.0093)***
Lag 1 employment	.898 (.005)***	.804 (.021)***	.003 (.014)	.626 (.033)***
Lag 1 wage	.874 (.008)***	.974 (.011)***	.167 (.057)***	.894 (.023)***
Observation	384	384	384	384
Firms	---	----	96	96

Standard errors in parentheses, **$p<0.05$, ***$p<0.01$