Final Report

THE IMPACT OF ICT ON EMPLOYMENT

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Humboldt-Innovation GmbH

Coordinator: Prof. Michael C. Burda, Ph.D.
Humboldt-Universität zu Berlin
Institut für Wirtschaftstheorie II
Spandauer Straße 1
D-10099 Berlin, Germany
Tel: +49 30 2093 5638
burda@wiwi.hu-berlin.de

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HUMBOLDT-UNIVERSITÄT ZU BERLIN

About the Authors

This research was conducted under the auspices of the Institut für Wirtschaftstheorie II, Humboldt Universität zu Berlin. The contributors are:

Part I: Growth Accounting, ICT, and Labor Demand
Battista Severgnini, M.Sc.

Part II: Offshoring
Dipl.-Vw. Sebastian Braun

Part III: ICT, Skills and Jobs
Dipl.-Vw. Dorothee Schneider

Executive Summary, editorial guidance, and overall project supervision:
Prof. Michael C. Burda, Ph.D.

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Executive Summary

After a considerable delay, the computer revolution – more precisely, the Information and Communications Technology (ICT) revolution – has arrived in Europe, with investment rising steadily, even overtaking the United States in some EU countries. This expenditure on office equipment, communications technology and software not only increases output directly, but appears to have an effect on total factor productivity (TFP) – sometimes called multi-factor productivity – or the effectiveness of factors of production when input levels are held constant. Especially in services like wholesale and retail trade, finance and insurance and business services, developments first evident in the United States have now begun to make themselves felt in Europe. Yet within the EU, ICT penetration has been remarkably heterogeneous – highest in Scandinavia, the Netherlands and the UK, less so for the rest of the continent, and the lowest in Mediterranean EU countries. It is thus also important to understand the reasons for this uneven adoption of ICT technologies. As total factor productivity represents the most important source of lasting improvements in standards of living (Hall and Jones 1999[1]) these developments forebode different long-run economic growth paths in the EU area.

Employment concerns continue to figure prominently in the European discussion regarding the adoption and implementation of new technologies, and still shape the current policy debate. In particular, one line of reasoning stresses that technical progress allows firms to produce the same output with less input – and especially less labor – leading to "technological unemployment." Careful economic analysis shows that aggregate output is not fixed, so that this "lump of demand fallacy" can be dismissed except for the shortest run; as a long-run proposition it is rejected by centuries of economic history. Yet unlike previous movements in European tradition dating back to the Luddites, current concerns are diffuse and more likely pointed at "globalization" than at the computer and the internet. All the same, the nexus between ICT and globalization is difficult to overlook. Internet, communication and logistic technologies are frequently intertwined with growing integration of international trade and disintegration of value added chains, and may lead to short-term job loss. Finally, hard scientific evidence shows that the distribution of income has become markedly less equal as a result of developments in both ICT and international trade.

From a purely theoretical viewpoint, little can be said *a priori* about the size or the magnitude of the net effect of ICT on employment. It represents the net outcome of many complex influences which can be more or less relevant under different assumptions. For example, to the extent that firms are unable to choose their output level, all forms of technical change which enhance productivity are likely to reduce the demand for labor, but only in the shortest of horizons. When firms are free to choose the level of output they produce, ICT will reduce the demand for labor only in the case of labor-saving technical progress. ICT might well represent labor-augmenting or neutral technical progress, in which case the demand for labor at any given labor cost

[1] Hall, R.E. and Jones, C.I. (1999), "Why Do Some Countries Produce So Much More Output per Worker than Others?", *The Quarterly Journal of Economics*, 114(1), 83-116.

increases. Furthermore, the quantitative extent of resulting fluctuations in employment will depend on the elasticity of *supply* of labor to the market under consideration. If labor supply to a particular labor market is highly elastic, these fluctuations will be pronounced; in the limiting case of inelastic supply to a labor market, the effect of TFP on employment is nil. These effects are likely to be different in the short-run than in the long-run, when households, firms and their representatives in collective bargaining have fully adjusted their behavior to the new circumstances.

The primary objective of this report is to evaluate and quantify the short and long-run effects of the ICT revolution on the labor market, in particular, on employment. In Part I we begin by presenting a number of stylized facts which have characterized the ICT revolution to date. These include the sharp declines in ICT prices, the upgrading of the educational attainment of employees as well as the widening of the income distribution. We then take the narrow perspective of ICT technology and its effect on labor demand, using basic and augmented specifications commonly employed in empirical research in personnel economics. We apply econometric methods to the EU KLEMS data at the industry and national level to estimate the average effect of ICT, measured in three different ways, on the *representative industry in a country* and the *representative EU country in a particular industry*. By estimating the specification within and across countries, an impression can be obtained for the heterogeneity as well as the precision of the effects to be estimated. In the Annex we present detailed estimates of these "reduced form" impact of technology and ICT investment for aggregate regions, individual EU countries and non-EU economies as well as for industries aggregated *across* EU industries. In doing so we also control for the role that product and labor market regulations can play in shaping employment impacts at country and industry level.

These econometric estimates comprise the core of our findings. While the estimates of labor demand are robust and uncontroversial – with statistically significant positive effects of output and negative effects of wages in most specifications – the effect of technology is highly dispersed around a small negative number and rarely statistically significant. Put differently, there is no evidence from our study of a systematically positive or negative long-run effect of ICT on employment, either among sectors within a single country, or across countries in a single sector. The high dispersion of the individual country and sector estimates should serve as a warning against expecting a uniform effect of ICT on employment. Rather – as the theory predicts – the effect on employment will depend on the particularities of the country or sector, including the supply of labor.

Recognizing the important role of ICT in integration of international trade, in Part II we study offshoring, the relocation of production processes and value added components in foreign countries, under the premise that the ICT has facilitated the rapid expansion of intermediate goods trade seen since the 1990s. As with ICT, offshoring can be seen as a shift in the aggregate production function. The effects of offshoring on employment are, however, far from obvious and involve a number of indirect feedback mechanisms, including complementarity of offshored processes with domestic operations (supply side) and increased foreign demand for domestic output (demand side). In addition to a detailed discussion of these theoretical effects, we perform a case study on the development of offshoring in the 1990s and its subsequent effect on the labor market using industry-level data from Germany. While economy-wide offshoring increased in the 1990s, there are pronounced differences across sectors. A first glance at the data suggests that the rise in offshoring is indeed associated with the ICT revolution. Labor demand equations support the hypothesis that offshoring has a negative effect on employment in manufacturing. In contrast, a positive association between offshoring and employment emerges in the service sector.

Finally, Part III looks at the effect of ICT on the distribution of income, especially for different levels of skill of labor. In addition to documenting recent developments in the EU and reviewing theories which account for these developments, it also outlines a well-established approach for discerning the effects of ICT on shares in aggregate compensation accruing to different types of labor. The results, obtained with EU KLEMS data, support the view that skill-biased technical change is a good characterization of the ICT revolution, although we cannot distinguish direct effects from indirect ones that might be induced by ICT and but in the end associated with offshoring. This evidence is consistent with evidence presented in Part I, but implies that the long-run supply of labor is relatively inelastic.

This report is meant to motivate and stimulate discussion and further work in the estimation of labor market effects of internet and communications technologies. In the end, an econometric estimate is only as good as the theory which underlies its specification, and the care with which the specification is laid out and the caveats understood. A great limitation of the present study, given the disparate findings across countries and sectors, is the level of aggregation of the data. With better data for a wider range of countries, this report could spur more detailed analyses of country and EU-wide effects of the ICT revolution. Enterprise-level data, combined with others related to the role played by institutions, could provide a clearer picture of the effects of the new technological era on employment.

Part I: Growth Accounting, ICT, and Labor Demand

I.1 Introduction

Several empirical studies have shown that, in the second half of the 1990s, the US economy was characterized by the introduction of new information and communication technologies (ICT) and, at the same time, by radical changes in the underlying structure of its economy. Moreover, the economy experienced, after an extended and unexpected delay, high levels of output growth accompanied by an impressive increase in multifactor and labor productivity growth. As noted by Stiroh (2002)[2] in a study on American industries, faster labor productivity growth and investment in ICT goods benefited not only the most modern sectors (retail, ICT equipment and the financial sectors) but also more traditional activities such as manufacturing. Dale Jorgenson and co-authors (2005)[3] have studied in detail this new phenomenon for the US and have identified five main stylized facts related to this new technological revolution:

1. A continuous and accelerating decline in the price of ICT goods, contributing to a boom in investments in new technologies;
2. A resurgence of economic growth associated with a strong, across-the-board productivity boom;
3. A change in the structure of the labor composition ratio and, at the same time, an increase of the quality of education;
4. Increasing wage differentials between skilled and unskilled workers;
5. Fragmentation of production processes across national boundaries.

Factors such as ICT investment and offshoring have played a central role in the strong US economic performance over the past decade. However, as noted in point 3 and 4, this new era has also been characterized by deep changes in the structure of the US labor market: the employment ratio of high-educated to low-educated workers has tripled over the last 20 years. At the same time, the wage premium of the skilled with respect to the unskilled has increased dramatically.

Even if the recent work by Jorgenson and associates shows a significant and positive relationship between ICT goods investment in the US on the one hand, and productivity, output growth and labor composition on the other - at both aggregate and industry levels - understanding the role

[2] Stiroh, K.J. (2002), "Information Technology and the US Productivity Revival: What Do the Industry Data Say?", *The American Economic Review*, 92(5), 1559-1576.
[3] Jorgenson, D.W., Ho, M. and Stiroh, K.J. (2005), "Information Technology and the American Growth Resurgence", *The MIT Press.*

of ICT as an engine of growth for the European economy represents an important challenge, especially when the causal effect of new technologies on employment are studied. Recently available aggregate and industry level data for each European country show very different evolutions of productivity and output growth. Moreover, it appears that in Europe a negative correlation between economic performance and the regulation of the labor and product market exists. For these reasons, the relation between the employment structure, the introduction of new technologies and the role of regulatory environment and economic institutions should be studied in a more detailed way. This approach has already been pursued by Blanchard and Wolfers (2000)[4] and Ljungqvist and Sargent (2003)[5], who have pointed out that there exist stark differences in the evolution of unemployment in Europe and the US. Earlier work on the reaction of the OECD to the oil shocks of the 1970s indicated low or even negative total factor productivity growth.[6] Moreover, the unemployment rate was higher in Europe because of the institutional framework adopted by some countries. In the same fashion, it may be useful to study how employment has reacted in European countries and whether different economic policies (especially product and labor market liberalizations) have been determinant in driving this new era of technological revolution, ostensibly the source of positive productivity shocks.

When employment is studied, especially in the area of labor demand analysis, it seems that the potential roles for the introduction of ICT investments in the EU context have not been adequately explored. The goal of Part I of this report is the presentation of a model framework for the analysis of the impact of ICT on employment as well as the econometric analysis conducted at the country and industry level. The econometric model proposed will take into account various theoretical problems encountered in the literature and the availability of data. The recent creation and development of the *KLEMS* datasets, i.e. databases containing measures of economic growth, productivity, employment creation, capital formation at the industry level, for most of the OECD countries not only contributes to our understanding of the most important features of productivity at the industry level. It can also help to detect the main causes for different employment growth rates in Europe and allows us to compare them with the stylized facts observable in other important world economies such as Australia, Japan, South Korea, and the US. Moreover, in this report we will try to disentangle the two effects produced by ICT investment. The first, measured by the standard classical growth accounting methodology, is related to capital accumulation. The second, which is arguably more important and more difficult to observe, is represented by the spillover in the economy by the vintage of ICT investment.

[4] Blanchard, O. and Wolfers, J. (2000), "The Role of Shocks and Institutions in the Rise of European Unemployment: The Aggregate Evidence", *Economic Journal*, 110, 1-33.
[5] Ljungqvist, L. and Sargent, T. (2003), "European Unemployment and Turbulence Revisited in a Matching Model", *New York University working paper.*
[6] See Bruno, M. and Sachs, J. (1985), *Economics of Worldwide Stagflation Cambridge*, Harvard University Press.

This first part of this chapter considers the analogies and differences between the European countries, divided into different geographical and institutional classifications, the US and, when it is possible, other countries, where we will exploit tools provided by econometrics and growth accounting analysis. Then, an important distinction between ICT capital accumulation and ICT spillover will be made, since the latter one is considered to be one of the most important determinants of growth in the last 15 years: Jorgenson and Stiroh (2003)[7] and Section 2.2 provide evidence for this hypothesis. Moreover, an analysis of how institutions can create or destroy jobs in an economy is presented. Finally, the last part of the section shows some caveats which can be faced when the econometric model is fed with data. It also gives suggestions for using a new dataset created by *EUROSTAT* in which data from household and enterprise surveys can give important information related to ICT usage and access and to the question of whether the skills related to new technologies (the so called *E-SKILL*) affect European economic growth.

Part I of this report is structured as follows: After defining information, communication and technology assets, Section 2 provides some stylized facts on similarities and differences between the US, the EU15 and other important world economies. Section 3 considers the most important contributions related to labor demand equations both when labor is treated as a homogenous input and when it is classified by skill, sex or age. Section 4 studies the role of technological change in the econometric specification as well as the properties and the limitations of the growth accounting analysis when the new input of ICT is introduced. Section 5 combines the main specifications with the detection of ICT-driven total factor productivity spillovers. Section 6 presents empirical results using the EU KLEMS dataset paying particular attention to the effect of ICT on employment. Section 7 describes the data and the variable used. Section 8 proposes a set of econometric specifications and presents the estimates for two countries, Germany and the United States. Moreover, it discusses econometric problems which can arise and proposes a number of variables collected by EUROSTAT in the ICT household and enterprise surveys as possible instruments in the empirical specification. Finally, we estimate error correction models in order to disentangle short- and long-run effects on employment and account for potential cointegration between the time series considered.

[7] Jorgenson, D.W. and Stiroh, K.J. (2003), "Raising the Speed Limit: US Economic Growth in the Information Age", *Brookings Papers on Economic Activity,* 1, 125-221.

I.2 US, EU and the World Economy during the ICT Era: Some Stylized Facts

This section will highlight the similarities and differences between the US, the EU and other countries of the world at the level of the aggregate economy in the past two to three decades. The stylized facts proposed in the previous section can be a useful starting point for understanding the variables which have been central sources of economic growth over the past fifteen years, as well as potential sources of differences in growth and employment performance within the European Union.

Before embarking on this analysis, it is essential to define the characteristics of information and communication technology (ICT) assets more precisely. Our attention is centered on capital stock estimates and especially on the decomposition of this stock into different types of assets. We adopt the conventions of the *EU KLEMS* manual[8], which are comparable to those of the National Income and Product Accounts (NIPA) produced by the US Bureau of Economic Analysis (BEA). Under this definition, it is possible to divide total assets into 11 different types as illustrated in Figure I.1. The ICT assets, which are marked in red in Figure I.1, are defined as the contribution of three different types of assets: two types of investment belonging to the tangible asset definition (i.e. *computing equipment* and *communications equipment*) and one related to intangible assets (e.g. *software*)[9]. As communications equipment includes very different types of goods ranging from radios, televisions, and telephones, to fiber optics and communications satellites, ICT is thus defined in a relatively broad fashion. This is in line with the findings by Triplett and Bosworth (2004)[10] and reflects the view of Timmer and van Ark (2005)[11] that the technological revolution can be also observed in office machines and related equipment. Moreover, this definition allows us to measure ICT goods since 1970 for most of the OECD countries.

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[8] Timmer, M.P., O'Mahony, M. and van Ark, B. (2007), "Growth and Productivity Accounts from EU KLEMS: an Overview", *National Institute Economic Review,* 200.

[9] The *Measuring Capital OECD manual* (2001) defines *tangible fixed assets* as "non-financial produced assets that consist of dwellings; other buildings and structures; machinery and equipment and cultivated assets", while *intangible fixed assets* are defined as "non-financial produced fixed assets that consist of mineral exploration, computer software, entertainment, literary or artistic originals and other intangible fixed assets intended to be used for more than one year."

[10] Triplett, J. and Bosworth, B. (2004), "Productivity in the US Services Sector. New Sources of Economic Growth", *The Brookings Institution*, Washington, DC.

[11] Timmer, M.P. and van Ark, B. (2005), "Does Information and Communication Technology Drive EU-US Productivity Growth Differentials?", *Oxford Economic Papers,* 57 (4), 693-716.

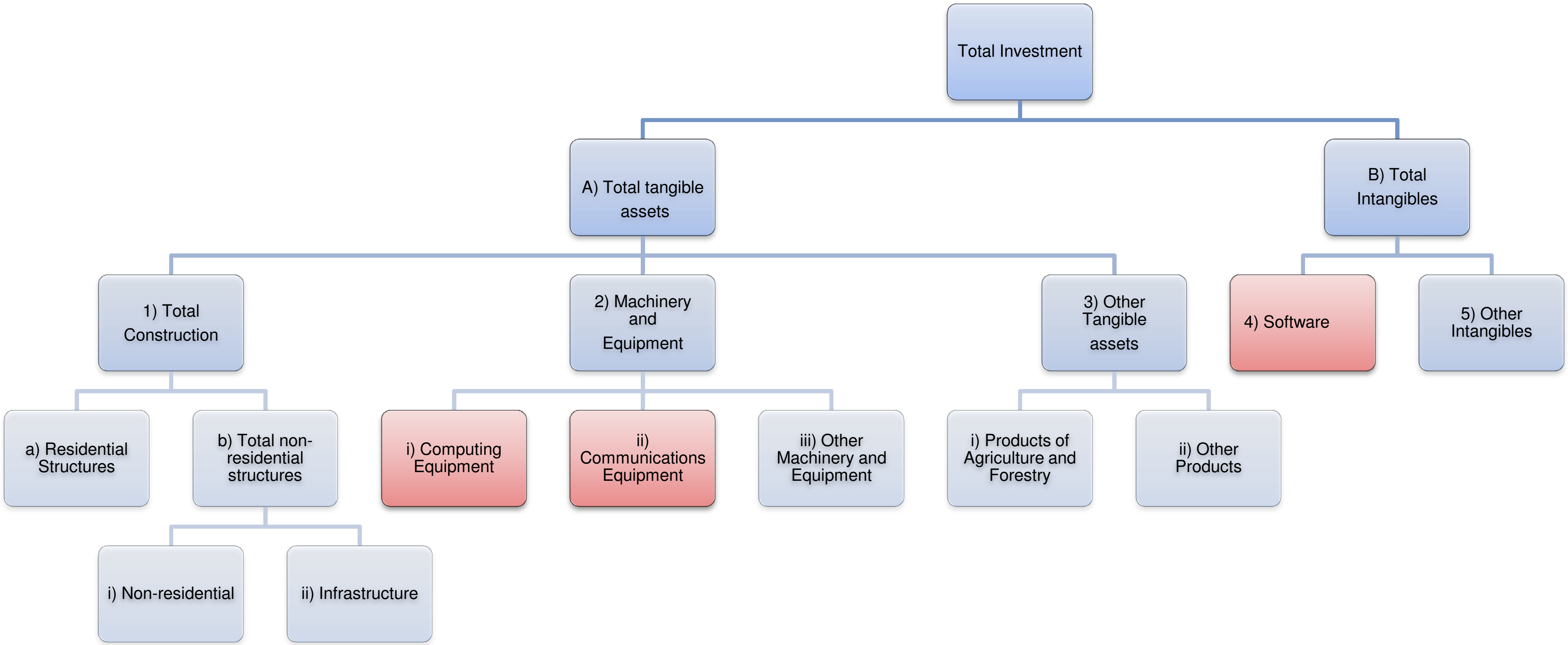


Figure I.1: List of asset types in the EU KLEMS database. ICT assets are marked in red.

I.2.1 First Stylized Fact: ICT Prices and Investment. Faster, Better and Cheaper

As documented in detail for the American case by Jorgenson et al. (2005)[12], ICT capital was characterized by a strong decline in the price of semiconductor technology, especially for computer and telecommunication equipment during the second half of the 1990s. This phenomenon is related to *Moore's Law*, which predicts that the power of the new chips doubles within 18-24 months, and appears to hold for ICT goods, which continue to become faster, better and cheaper. Unfortunately price series are not publicly available for most of the European countries: in order to compare whether also in Europe this positive technological shock did appear after 1995, we use the most recent data available for the aggregate level of the European Union[13] from van Ark et al. (2003)[14], which cover the period 1990-2000, and were constructed from the ratio of the changes in current and constant price series from the *OECD NATIONAL ACCOUNTS*. Using these data, we compute in Table I.1 the growth rate of the Price Indexes of Gross Fixed Non-Residential Capital Formation by asset type. The main differences in growth rates are observable for non-ICT capital, with faster price increases observed for transport equipment and non-residential structures. ICT prices have been decreasing since 1990 and display a very similar growth rate in the US and the EU.

[12] Jorgenson, D.W., Ho, M. and Stiroh, K.J. (2005), "Information Technology and the American Growth Resurgence", *The MIT Press.*

[13] In this case, for European Union we consider a weighted average for all the EU 15 with the exclusion of Belgium, Luxembourg and Greece.

[14] Van Ark, B., Melka, J., Mulder, N., Timmer, M. and Ypma, G. (2003), "ICT Investments and Growth Accounts for the European Union", *Research Memorandum* GD-56.

Table I.1: Cumulative change in price indexes for gross fixed non-residential capital formation by asset type, 1980-2000

Asset type	1980-1985	1985-1990	1990-1995	1995-2000	1980-2000
Office and Computer Equipment					
European Union	-34.6	-21.9	-38.0	-68.1	-89.9
United States	-35.3	-21.0	-37.8	-67.6	-89.7
Communication Equipment					
European Union	28.7	2.9	-4.3	-15.5	7.1
United States	24.1	5.5	-3.4	-13.2	9.7
Software					
European Union	17.6	-2.0	-2.3	-3.6	8.5
United States	13.4	-5.6	-5.8	-3.6	-2.8
Total ICT					
European Union	-5.1	-9.3	-16.8	-35.1	-53.5
United States	-8.0	-8.9	-18.4	-33.5	-54.5
Non-ICT Equipment					
European Union	33.3	10.0	7.4	-0.1	57.2
United States	23.6	18.3	13.3	9.4	81.1
Transport Equipment					
European Union	39.9	24.9	13.9	5.9	110.7
United States	28.9	11.9	19.7	3.0	77.8
Non-Residential Buildings					
European Union	29.8	24.5	12.1	11.2	101.3
United States	23.6	16.6	12.8	18.2	92.0
Total Non-Residential GFCF					
European Union	28.2	14.7	6.4	-2.0	53.3
United States	17.6	10.2	4.9	-3.2	31.7

Source: Authors' calculations using data reported by van Ark and al. (2003)

More recent calculations on ICT prices at the country level have been provided by Cette et al. (2008)[15] and are presented in Table I.2. The authors compared the average annual ICT price growth, computed as the weighted average of the price trends of computer hardware, software and communication equipment for 4 different countries (France, Japan, United Kingdom and United States). While the magnitude of the price decrease was about the same for the United Kingdom and the United States, it was weaker for France and stronger for Japan. However, one can observe that the highest drop happened in the period 1995-2000 and that the strong negative trend was observed in all countries.

[15] Cette, G., Kocoglu, Y. and Mairesse, J. (2008), "A Comparison of Productivity Growth in France, Japan, the United Kingdom and the United States over the Past Century", paper presented at the Conference "Banque de France-Bank of Japan: Converging views", Paris, January 8th.

Table I.2: Average annual ICT price growth (in %) in France, the United Kingdom, the United States and Japan, 1980-2005

	1980-1990	1990-1995	1995-2000	2000-2005	1980-2005
France	-1.5	-5.8	-6.7	-4.5	-4.0
Japan	-3.5	-6.6	-9.5	-5.3	-5.7
United Kingdom	-3.5	-5.9	-8.2	-4.8	-5.2
United States	-3.5	-5.4	-7.4	-4.3	-4.8

Source: Cette, Kocoglu and Mairesse (2008)

Finally, the second part of this stylized fact relates ICT price decrease to higher investment in new technologies. Table I.3 and Table I.4 consider two measures of new technology penetration for most of the EU countries: the first one is a stock measure and is the ICT capital compensation, expressed in terms of the share in total compensation. The second is a flow measure captured by the growth rate of ICT investment. Looking at the first measure in Table I.3, a gap is apparent between the US and the data for the aggregate EU15, i.e. the EU member states as of January 1995 (Austria, Belgium, Denmark, Spain, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Sweden), plus two EU10 countries (Czech Republic and Slovenia) and other countries (Australia, Japan, South Korea and United States). The US shows on average more than 4% higher ICT capital compensation also when compared to countries like Australia, Japan and South Korea. However, a detailed examination of the data at the country level (for the total economy)[16] reveals a very heterogeneous picture, with ICT penetration levels ranging from very low levels in Ireland and Italy to EU leaders including Denmark, Sweden and the UK.

[16] For this part, the EU KLEMS dataset provides complete data for all the EU 15 except for Greece.

Table I.3: Share of ICT capital in total annual compensation of capital, 1980-2005

Country	1980-1985	1985-1990	1990-1995	1995-2000	2000-2005
Austria	5.3	6.6	7.9	8.9	9.4
Belgium	8.5	11.1	11.6	12.8	13.9
Denmark	**10.4**	**14.1**	**13.7**	10.4	10.2
Finland	6.6	8.8	10.2	8.5	10.7
France	5.5	7.5	8.0	10.5	10.8
Germany	7.9	9.6	10.9	13.8	10.8
Ireland	2.8	4.0	4.7	6.6	5.7
Italy	6.5	7.3	7.5	7.2	7.8
Luxembourg	6.4	10.2	10.8	11.1	13.0
Netherlands	5.5	8.0	10.7	12.2	13.0
Portugal	2.0	3.0	5.8	8.6	11.1
Spain	8.1	9.4	10.7	12.4	13.1
Sweden	n.a.	n.a.	11.9	14.1	16.7
United Kingdom	5.5	10.4	11.4	16.1	**18.6**
EU15	6.5	8.6	9.4	10.5	11.5
EURO AREA	6.5	8.1	8.8	9.2	9.9
Czech Republic	n.a.	n.a.	n.a.	10.1	10.6
Slovenia	n.a.	n.a.	n.a.	**16.5**	14.9
Australia	6.4	8.0	9.2	11.8	13.1
Japan	5.3	6.6	8.0	9.9	10.6
South Korea	3.4	5.0	9.2	7.4	11.2
USA	7.9	10.8	12.5	15.1	15.7

Note: (Underlined and bold figures indicate minimum and maximum of the EU countries in each sub-period).

Source: Authors' calculations using the EU KLEMS dataset.

Another indicator which may be useful to consider is the ratio of investment in ICT to value added for the countries whose investment series are available. It is evident that - except for the very low performance in Italy - ICT penetration was booming with a double digit growth rate in all countries in the period 1995-2000.

Table I.4: Average annual real growth of ICT investment in selected periods, 1990-2005 (%)

Country	1990-1995	1995-2000	2000-2005
Austria	5.7	24.3	7.4
Czech Republic	n.a.	18.3	-1.1
Denmark	11.4	15.7	1.5
Finland	0.3	18.1	6.5
Germany	-1.8	16.9	6.2
Italy	3.4	3.9	7.7
Netherlands	3.4	31.1	6.7
Sweden	10.5	10.0	0.7
United Kingdom	-0.4	16.4	6.7
Australia	8.9	19.6	13.5
Japan	-1.3	13.0	-0.6
South Korea	0.7	19.9	5.3
USA	6.0	21.2	3.8

Source: Authors' calculations using the EU KLEMS dataset.

As remarked by this first stylized fact, the high decrease in ICT prices during the period 1995-2000 encouraged ICT investment in the US, EU and in the most advanced world economies thereby increasing the ICT capital compensation at the total economy level.

I.2.2 Second Stylized Fact: Productivity Boom and Output Growth: Tigers and Tortoises

The second stylized fact provides evidence of the impact of ICT on the productivity and output growth. Several articles have already stressed the crucial role of the new technology for boosting productivity and the resurgence of several economies: Jorgenson (2001)[17] has shown that ICT investments are the key for the growth of the American economy; moreover, Ahmad, Schreyer and Wolfl (2004)[18] and Piatkowski and van Ark (2005)[19] respectively provide evidence for OECD countries, Eastern Europe and the former Soviet Union.

In this section, we will exploit the most updated *EU KLEMS* dataset version, released in March 2008, in order to replicate the exercise proposed by Jorgenson and Vu (2005)[20] for the EU countries. Table I.5 represents the contribution of capital and labor input and total factor

[17] Jorgenson, D.W. (2001), "Information Technology and the US Economy", *American Economic Review*, 91(1), 1-32.
[18] Ahmad, N., Schreyer, P. and Wolfl, A. (2004), "ICT Investment in OECD Countries and its Economic Impact", Chapter 4 in OECD, "*The Economic Impact of ICT: Measurement, Evidence, and Implications*", 2004, Paris.
[19] Piatkovski, M. and Van Ark, B. (2005), "ICT and Productivity Growth in Transition Economies: Two-phase Convergence and Structural Reforms", *TIGER Working Paper Series* No.72, Warsaw.
[20] Jorgenson, D.W. and Vu, K. (2005), "Information Technology and the World Economy", *Scandinavian Journal of Economics,* 107(4), 631-650.

productivity growth to economic growth (in the second row in italics you find the respective contribution to output growth in percent) at the total economy level for most of the EU15 and four relevant non European countries (Australia, Japan, Korea and the US) during a 15 year period (1990-2005). As a measure of economic output growth we consider the growth rate of value added volume (in % per year); the contribution of capital inputs is divided into ICT and non-ICT, while labor input is defined as the contribution of labor services, i.e. hours worked without adjustment for skills and other labor characteristics, to value added growth. Moreover, total factor productivity growth is computed as the difference of the output growth and the observable inputs following the methodology that will be described in more detail in Section 4.

The sample was divided into three sub periods of six years: 1990-1995, 1995-2000 and 2000-2005. From Table I.5 it can be seen that during the initial period 1990-1995, output grew at approximately 2% per year in Europe, the US, and Japan. After 1995, however, the growth rate in the US exceeded by about 1% the EU15 average annually. Moreover, investigating the data in a more detailed way, the composition of output growth is striking: for the period 1990-2000, input growth accounted in the US and the EU respectively for more than 80% and 60% of the total economic growth with capital being the most important input for the growth in Europe. Capital represents more than 55% of the total contribution to output growth, the contribution of productivity stands at 40% and only a small fraction is due to labor growth. This is a peculiar picture, since we can see that - except for Japan - in other countries like South Korea and the US, labor played an important role as a source of economic growth. Furthermore, the contribution of ICT capital is rather small (about one fourth) compared to the contribution of non-ICT capital. However, in the last period these shares have shifted: productivity accounts for about 55% of total growth in the US, while in Europe this contribution declined to only 15 %.

From these stylized facts, it appears that the US has indeed benefited more from ICT investments than Europe over the past decade. However, as Table I.5 shows, if we consider individual countries, the picture is not at all uniform for European countries: in the Nordic area (Finland, Denmark, and Sweden) and Continental Europe (France, Netherlands and Germany), ICT contribution has been much higher than in the Mediterranean countries.

Table I.5: Average annual contribution of capital and labor input and total factor productivity growth to economic growth: European aggregate and non European total economy data, 1990-2005.

	1990-1995					1995-2000					2000-2005				
COUNTRY	*Y*	*TFP*	*KICT*	*KNICT*	*N*	*Y*	*TFP*	*KICT*	*KNICT*	*N*	*Y*	*TFP*	*KICT*	*KNICT*	*N*
EU15	1.9	0.7	0.3	0.8	0.1	2.6	0.5	0.5	0.8	0.8	1.8	0.3	0.4	0.6	0.6
	100.0	38.3	14.4	41.5	5.9	100.0	18.4	21.1	29.3	31.3	100.0	15.2	20.1	34.8	29.9
EURO	1.9	0.7	0.2	0.8	0.2	2.4	0.5	0.4	0.8	0.7	1.7	0.2	0.3	0.7	0.5
	100.0	34.9	12.2	44.4	8.5	100.0	20.7	18.2	31.4	29.8	100.0	14.4	17.8	40.2	27.6
Australia	2.3	0.6	0.5	0.6	0.6	4.3	1.2	0.9	0.9	1.3	3.0	-0.4	0.9	1.1	1.4
	100.0	24.3	21.6	26.7	27.4	100.0	28.3	20.7	21.7	29.3	100.0	-12.6	29.3	37.0	46.3
Japan	2.1	0.2	0.3	1.9	-0.2	1.2	0.0	0.4	1.0	-0.3	1.4	0.4	0.3	0.8	-0.2
	100.0	8.0	12.6	90.0	-10.6	100.0	3.7	36.6	82.0	-22.3	100.0	31.7	24.1	57.4	-13.1
Korea	7.6	2.5	0.2	2.3	2.7	4.7	2.1	0.2	1.4	1.0	4.8	1.7	0.3	1.1	1.6
	100.0	32.3	2.6	29.8	35.3	100.0	43.8	4.7	30.8	20.7	100.0	36.3	5.8	23.9	34.0
USA	2.1	0.4	0.4	0.6	0.7	3.5	0.4	0.7	0.9	1.6	2.9	1.6	0.5	0.6	0.2
	100.0	17.3	18.3	31.4	33.0	100.0	10.8	20.3	25.0	43.9	100.0	55.9	18.3	19.4	6.4

Source: Authors' calculations using the EU KLEMS dataset

Table I.6: Average annual growth contributions of capital input, labor input and total factor productivity growth: EURO 15 country level total economy data, 1990-2005.

	1990-1995					1995-2000					2000-2005				
COUNTRY	Y	TFP	KICT	KNICT	N	Y	TFP	KICT	KNICT	N	Y	TFP	KICT	KNICT	N
Austria	2.8	1.1	0.3	0.7	0.7	2.6	0.9	0.5	0.5	0.6	1.9	0.6	0.4	0.4	0.6
	100.0	37.9	11.3	26.7	24.1	100.0	35.2	20.6	19.3	24.9	100.0	29.1	20.8	20.0	30.1
Belgium	1.6	-0.1	0.4	1.0	0.4	2.3	-0.2	0.9	0.7	0.9	1.9	-0.2	0.7	0.7	0.7
	100.0	-6.1	25.9	58.1	22.2	100.0	-10.3	39.3	32.5	38.5	100.0	-10.5	35.5	36.3	38.8
Denmark	1.5	0.8	0.6	0.2	-0.2	2.4	-0.5	1.1	0.4	1.4	1.5	0.2	0.6	0.3	0.2
	100.0	56.7	42.9	15.7	-15.4	100.0	-19.7	44.0	16.2	59.5	100.0	16.3	43.9	23.5	16.3
Spain	2.1	-0.1	0.3	1.2	0.7	3.4	-0.6	0.5	1.3	2.3	3.3	-0.7	0.3	1.5	2.2
	100.0	-3.8	13.4	58.9	31.5	100.0	-17.6	14.2	36.3	67.1	100.0	-21.9	9.9	45.2	66.8
Finland	-1.2	0.8	0.2	0.2	-2.4	4.3	1.6	0.6	0.5	1.6	2.7	1.2	0.5	0.4	0.7
	100.0	-63.0	-16.9	-17.1	197.0	100.0	37.9	13.2	10.9	38.1	100.0	43.2	17.5	14.7	24.6
France	1.3	0.1	0.2	0.6	0.5	2.4	0.7	0.3	0.5	0.9	1.9	0.7	0.3	0.6	0.3
	100.0	6.2	12.9	44.4	36.5	100.0	29.8	13.3	19.9	37.0	100.0	35.1	14.4	33.3	17.2
Germany	2.7	1.1	0.3	1.3	0.0	1.7	0.5	0.5	0.9	-0.2	1.2	0.6	0.3	0.5	-0.3
	100.0	41.2	9.9	47.7	1.2	100.0	30.7	27.9	54.6	-13.1	100.0	49.8	28.3	46.5	-24.6
Ireland	n.a.	n.a.	n.a.	n.a.	n.a.	9.3	2.2	0.8	3.2	3.1	6.0	0.0	0.2	3.7	2.1
	n.a.	n.a.	n.a.	n.a.	n.a.	100.0	23.7	8.7	34.3	33.3	100.0	-0.8	3.9	61.6	35.4
Italy	1.1	0.8	0.1	0.5	-0.3	1.6	0.0	0.3	0.6	0.7	1.1	-0.5	0.2	0.7	0.6
	100.0	69.4	12.9	47.1	-29.4	100.0	2.5	19.7	35.7	42.1	100.0	-43.7	17.3	67.2	59.2
Luxembourg	5.3	1.3	0.2	1.4	2.4	4.3	-0.9	0.5	1.8	2.8	4.1	0.0	0.7	1.2	2.2
	100.0	24.2	4.0	26.9	45.0	100.0	-20.6	12.8	42.0	65.8	100.0	0.7	17.0	29.4	52.9
Netherlands	2.3	0.1	0.4	0.6	1.2	3.6	0.3	0.7	0.8	1.9	1.7	0.6	0.4	0.3	0.4
	100.0	3.0	18.1	27.7	51.2	100.0	7.3	20.1	21.2	51.3	100.0	37.1	22.5	17.6	22.8
Portugal	n.a.	n.a.	n.a.	n.a.	n.a.	3.5	0.5	1.0	2.0	0.1	1.3	-1.6	0.6	1.3	1.1
	n.a.	n.a.	n.a.	n.a.	n.a.	100.0	14.3	27.4	56.4	1.9	100.0	-125.8	44.5	98.7	82.6
Sweden	4.0	1.2	0.6	1.0	1.1	3.3	0.5	0.6	1.3	0.8	2.8	1.3	0.3	0.9	0.3
	100.0	30.2	15.5	25.8	28.5	100.0	14.1	19.4	40.5	26.0	100.0	44.9	11.9	31.0	12.2
UK	1.5	1.2	0.4	0.5	-0.6	3.1	0.2	0.9	0.8	1.2	2.5	0.4	0.6	0.5	0.9
	100.0	80.1	25.9	34.9	-40.9	100.0	7.2	29.3	25.0	38.4	100.0	15.1	26.1	20.4	38.4
EU15	1.88	0.72	0.27	0.78	0.11	2.56	0.47	0.54	0.75	0.8	1.84	0.28	0.37	0.64	0.55

Source: Authors' calculations using the EU KLEMS dataset

I.2.3 Third Stylized Fact: Changes in the Labor Composition and Educational Attainment

In this subsection, the changing composition of employment is analyzed. The evidence provided by Jorgenson and associates for the US and by Leitner and Stehrer (2008)[21] for the EU KLEMS countries shows the presence of a skill-biased technological change: the introduction of new ICT capital in the production function shifts relative demand towards higher educated workers. In order to measure this effect, two indicators are considered: labor quality and the growth rate of the skilled and the unskilled in the economy. The growth rate of labor quality ΔLQ is derived as the difference of the growth rate of the labor input (number of employees) minus hours worked, i.e.

$$\Delta LQ = \Delta lnN - \Delta lnH \qquad \text{(I.1)}$$

The expectation is that new technologis increase labor quality since firms will shift their share of total hours worked towards higher skilled workers who have a better knowledge of the new technologies introduced. Following the approach introduced by Jorgenson et al. (1987)[22], these statistics take into account that all labor inputs are quality adjusted[23]. Table I.7 displays the statistics for the average annual growth rate of the aggregate labor input, hours worked and the labor quality: except for South Korea, especially in the two most recent periods it is possible to observe a reallocation of labor demand. The rate of hours worked grows at a slower speed than labor inputs, thereby increasing labor quality.

[21] Leitner, S. and Stehrer, R. (2008), "Changes in the Composition of Labor", *WIIW working paper,* presented at the Final EU KLEMS Conference, Groningen.
[22] Jorgenson, D.W., Gollop, F. and Fraumeni, B. (1987), "Productivity and US Economic Growth", *Harvard University Press.*
[23] For this reason, some statistics related to labor input and reported in Section 2.2 can differ from the one displayed in this section.

Table I.7: Average annual change in labor composition, 1990-2005.

Country	Type of input	1990-1995	1995-2000	2000-2005
EU15	Labor input	0.0	1.4	1.1
	Hours	-0.3	1.1	0.7
	Labor quality	*0.3*	*0.3*	*0.4*
EURO	Labor input	0.3	1.4	1.1
	Hours	0.0	1.0	0.7
	Labor quality	*0.3*	*0.4*	*0.5*
Australia	Labor input	0.5	2.1	2.4
	Hours	0.5	2.0	2.1
	Labor quality	*0.0*	*0.1*	*0.3*
Japan	Labor input	2.0	0.3	3.0
	Hours	-0.2	0.1	2.3
	Labor quality	*2.2*	*0.2*	*0.7*
South Korea	Labor input	3.7	3.6	3.7
	Hours	3.3	3.8	3.8
	Labor quality	*0.4*	*-0.2*	*-0.1*
USA	Labor input	0.9	2.3	0.6
	Hours	0.8	2.3	0.1
	Labor quality	*0.1*	*0.0*	*0.5*

Source: Authors' calculations using the EU KLEMS dataset

Table I.8, which shows the same statistics for most EU countries, reveals a strong positive correlation between ICT penetration, as measured in subsection 2.1, and labor quality, since in the Nordic countries and in France and Germany, the ICT share seems to be associated with a higher reallocation between labor input and hours.

Table I.8: Average annual change in labor composition, 1990-2005

Country	Type of input	1990-1995	1995-2000	2000-2005
Austria	Labor input	1.1	0.8	0.6
	Hours	0.8	0.3	0.5
	Labor quality	*0.3*	*0.6*	*0.1*
Belgium	Labor input	-0.1	1.1	1.1
	Hours	-0.6	1.0	1.0
	Labor quality	*0.5*	*0.1*	*0.1*
Czech Republic	Labor input	n.a.	-2.0	0.0
	Hours	n.a.	-1.3	-0.9
	Labor quality	*n.a.*	*-0.7*	*0.9*
Denmark	Labor input	-0.2	3.9	3.8
	Hours	-0.8	3.6	3.2
	Labor quality	*0.6*	*0.3*	*0.6*
Spain	Labor input	0.4	2.5	1.2
	Hours	0.4	2.5	1.0
	Labor quality	*0.0*	*0.0*	*0.2*

Finland	Labor input	-4.3	1.4	1.0
	Hours	-4.7	1.0	0.2
	Labor quality	*0.4*	*0.4*	*0.8*
France	Labor input	0.4	0.5	0.0
	Hours	0.4	-0.5	-0.7
	Labor quality	*0.0*	*1.0*	*0.7*
Germany	Labor input	0.5	1.1	0.7
	Hours	-0.2	1.6	0.1
	Labor quality	*0.7*	*-0.6*	*0.6*
Hungary	Labor input	-2.6	5.8	3.6
	Hours	-1.7	5.4	3.2
	Labor quality	*-0.9*	*0.4*	*0.4*
Ireland	Labor input	2.0	0.6	1.7
	Hours	3.0	0.9	1.3
	Labor quality	*-1.0*	*-0.3*	*0.4*
Italy	Labor input	-0.1	0.1	-0.1
	Hours	-0.1	-0.8	-0.7
	Labor quality	*0.0*	*0.9*	*0.6*
Luxembourg	Labor input	3.2	2.9	0.6
	Hours	3.0	2.4	0.1
	Labor quality	*0.2*	*0.5*	*0.5*
Netherlands	Labor input	1.4	1.6	0.9
	Hours	1.1	1.3	0.9
	Labor quality	*0.4*	*0.3*	*0.1*
Portugal	Labor input	0.8	-0.6	0.6
	Hours	-0.4	-0.6	0.6
	Labor quality	*1.3*	*0.0*	*0.0*
Sweden	Labor input	-2.6	0.7	0.8
	Hours	-1.9	1.0	0.1
	Labor quality	*-0.8*	*-0.4*	*0.7*
United Kingdom	Labor input	-1.0	1.7	1.0
	Hours	-1.6	1.6	0.8
	Labor quality	*0.7*	*0.1*	*0.2*

Source: Authors' calculations using the EU KLEMS dataset

In Table I.9 we divide the growth rate of total hours worked into two types: skilled and unskilled. Unskilled labor is defined as those workers who have at most completed lower secondary school, while skilled labor is defined as all workers with an educational attainment above lower secondary school. In this case, we can observe that the phenomenon is similar for all the countries: significant growth in skilled labor demand juxtaposed against modest decreases in unskilled labor. These data are also suggestive of an increasing trend in demand for skilled workers and steeper declines in unskilled employment.

Table I.9: Annual growth rate in skilled and unskilled labor, 1990-2005

Country	1990-1995		1995-2000		2000-2005	
	Skilled	Unskilled	Skilled	Unskilled	Skilled	Unskilled
Austria	4.3	-0.4	4.5	-0.5	2.5	-0.4
Belgium	5.2	-0.6	2.9	-0.4	1.6	-0.3
Denmark	5.6	-0.3	3.1	-0.6	3.3	-0.8
Spain	4.0	-0.6	1.1	-0.5	1.1	-0.6
Finland	4.7	-1.8	3.8	-0.5	2.6	-0.4
France	4.7	-0.5	1.3	-0.1	1.0	-0.1
Germany	2.6	-0.2	2.0	-0.4	3.3	-0.8
Ireland	2.1	-0.2	5.1	-0.5	4.9	-0.6
Italy	2.7	-0.2	3.4	-0.9	2.9	-0.9
Luxembourg	6.5	-1.1	6.9	-0.7	2.7	-0.4
Netherlands	3.9	-0.3	-3.4	0.3	5.7	-0.6
Portugal	1.4	-0.1	3.1	-0.5	5.0	-1.1
Sweden	1.5	-0.2	2.9	-0.4	6.2	-1.2
United Kingdom	6.6	-0.8	4.6	-0.7	3.7	-0.8
EU15	3.3	-0.4	3.6	-0.5	3.2	-0.5
EURO	2.3	-0.2	3.3	-0.4	3.0	-0.5
Czech Republic	0.0	0.0	1.3	-0.2	3.0	-0.4
Hungary	0.0	0.0	5.2	-0.7	4.5	-0.9
Australia	6.1	-0.9	3.2	-0.6	2.5	-0.6
Japan	2.4	-0.5	5.7	-2.9	3.4	-2.5
Korea	3.1	-1.1	-1.2	0.2	2.2	-0.4
USA	1.4	-0.5	1.4	-0.5	1.6	-0.7

Source: Authors' calculations using the EU KLEMS dataset

I.2.4 Fourth Stylized Fact: Inequality between Skilled and Unskilled

To the extent that rising employment of skilled workers reflects shifts in relative demand, standard models of the labor market would predict an increase in the skill premium, i.e. the relative wage between skilled and unskilled. Indeed, especially for the US and the UK, rising demand for skilled workers has been accompanied by a significant increase in their wage and compensation relative to the unskilled. Table I.10 displays annual growth rates of the wage differential. While the same trend that has been observed in the United States is evident in the EU, it is more moderate, and hides significant heterogeneity. In one group of countries (Italy, Portugal and the Eastern European countries) the wage differential is increasing, while for other groups (Continental EU and Mediterranean EU) it is more or less stable over time.

Table I.10: Annual growth change of wage differential, 1990-2005.

Country	1990-1995	1995-2000	2000-2005
Austria	3.3	0.5	1.8
Belgium	4.0	2.2	4.0
Denmark	-1.8	2.2	4.5
Spain	6.2	6.7	6.2
Finland	-2.1	6.9	4.1
France	4.4	0.6	-1.7
Germany	6.7	2.4	3.2
Ireland	10.4	7.6	10.3
Italy	14.7	7.0	11.1
South Korea	9.8	4.2	6.3
Luxembourg	4.0	13.7	10.9
Netherlands	3.7	5.6	4.8
Portugal	3.4	10.1	2.9
Slovenia	n.a.	7.5	6.9
Sweden	6.0	1.6	1.3
United Kingdom	5.2	4.9	-0.6
Czech Republic	n.a.	8.6	6.7
Hungary	n.a.	18.2	12.0
Australia	3.4	6.6	6.0
Japan	3.6	-3.9	-1.4
USA	6.2	6.2	5.9

Source: Authors' calculations using the EU KLEMS dataset

More details related to the third and the fourth stylized facts can be found in Part III of this report.

I.2.5 Fifth Stylized Fact: Outsourcing

The ICT revolution has changed the nature of international trade. ICT is frequently seen as the main driving force behind the recent wave of globalization, which is characterized by the diffusion of production stages across national boundaries. In this context, ICT enables the coordination of tasks performed at different locations, facilitates the transmission of instructions and permits the electronic transmission of certain types of output. These developments enable firms to take advantage of international cost differences and induce them to offshore parts of their production activities.

The share of imported intermediates in total inputs can serve as an indicator of offshoring.[24] Unfortunately, harmonized input-output tables that serve as a basis for these indices are

[24] The indicator choice is rationalized in Section 4 of Part II of this report.

updated only every 5 years and the last year available is 2000. Despite these limitations, Table I.11 illustrates that for most of the countries, offshoring has indeed been on the rise in the second half of the 1990s. Table I.11 also shows that the prevalence of offshoring differs widely between countries with offshoring being particularly important in smaller countries.

Table I.11: Index of offshoring of goods and services

Country	1995	2000
Austria	0.60	0.70
Belgium	0.71	0.81
Denmark	0.56	0.61
Spain	0.32	0.41
Finland	0.37	0.43
France	0.34	0.30
Germany	0.34	0.44
Italy	0.33	0.40
Netherlands	0.66	0.69
Sweden	0.53	0.61
UK	0.44	0.50
Japan	0.10	0.12
United States	0.14	0.19

Source: OECD (2007), OECD, Input-Output database

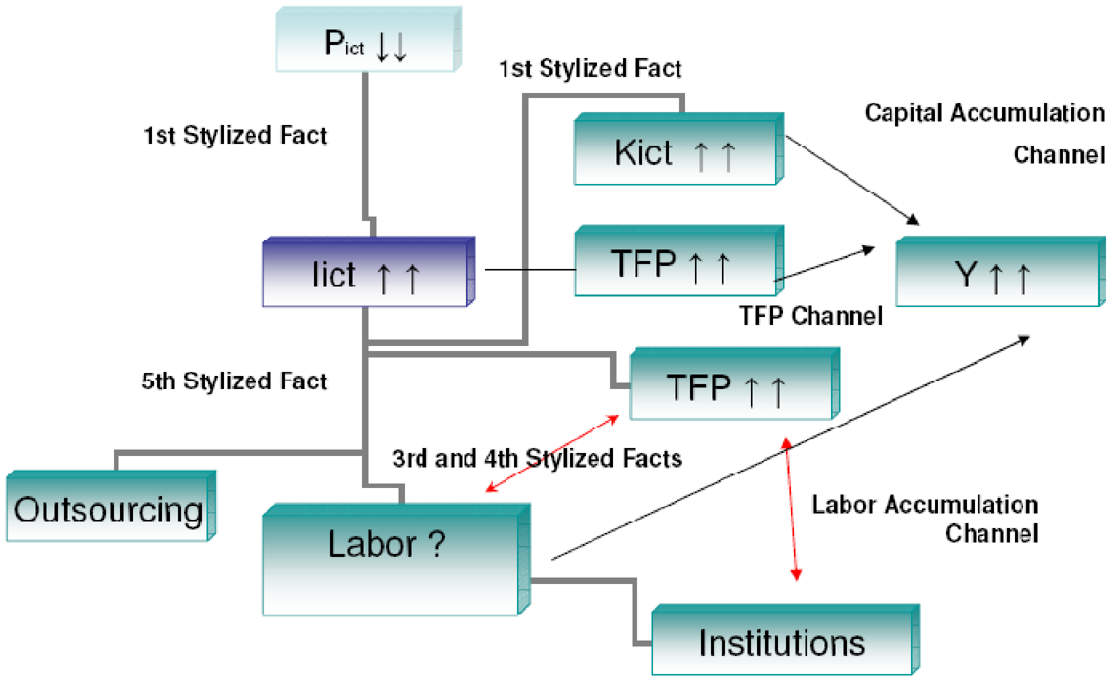
I.2.6 Summary

Having illustrated these 5 stylized facts, the following conclusions can be drawn which will be important for the analysis to follow:

1. The decline of ICT prices was a common, exogenous, and international phenomenon for those countries open to international trade.
2. ICT penetration has been different for each country considered, especially after 1995. As in the US, the Nordic and Continental European area have experienced higher levels of ICT investment, while Mediterranean Europe has lagged behind until the 2000-2005 period.
3. ICT penetration is correlated with TFP growth, which is the most important source of long-run growth. Moreover, ICT capital accumulation has also increased its contribution to output growth.
4. Also labor composition has radically changed in terms of labor quality with a shift of the share in total hours worked towards higher skilled workers who have a better knowledge of the newly introduced technologies. At the same time the inequality between skilled and unskilled workers has increased.
5. Production chains are increasingly global and fragmented across national boundaries. ICT is considered to be a main driving force of this development.

Figure I.2 represents a summary of these stylized facts. In this first part of the report we want to investigate whether a channel between the TFP created by ICT and total employment exists and whether it has a positive impact; in other words, we study whether employment and productivity are complements or substitutes. Previous studies at the macro level[25] claim that this channel exists and that employment is highly influenced by technological change and not by capital accumulation itself. Moreover, popular opinion tends to associate high productivity growth (and high technological capital accumulation) with *decreases* in employment. On the other hand, a faster acceleration in output growth can be reconciled with positive capital input and productivity growth. For these reasons, it is also important to study the role of the institutions which can stimulate or delay the accumulation of capital, the adoption of new technologies and the expansion of output overall.

Figure I.2: Summary of stylized facts



[25] For example, Krusell, P., Ohanian, L.E., Rios-Rull, J.V. and Violante, G.L. (2000), "Capital-Skill Complementarity and Inequality: A Macroeconomic Analysis", *Econometrica*, 68, 1029-1053.

From a theoretical point of view, ICT could have both a micro and a macroeconomic impact on employment. At a firm or industry level, new technology can increase productivity and outsourcing; at a macro level, we can also observe other effects on the general structure of employment related to spillover and product and labor market regulation.

A graphical explanation can help to illustrate the theoretical effects of ICT on employment. Figure I.3 shows two different effects of technology on employment. On the left part of the Figure, technological progress causes the demand for labor to shift rightwards if technical progress is labor augmenting or neutral. On the other hand, the right part of the figure shows the case when technology is labor saving: in this case, it decreases the wage level. Summarizing, when the labor supply is fixed, a positive technological change creates more wage inequality, but does not affect the level of employment.

Figure I.3: Theoretical effects of ICT when labor supply is inelastic.

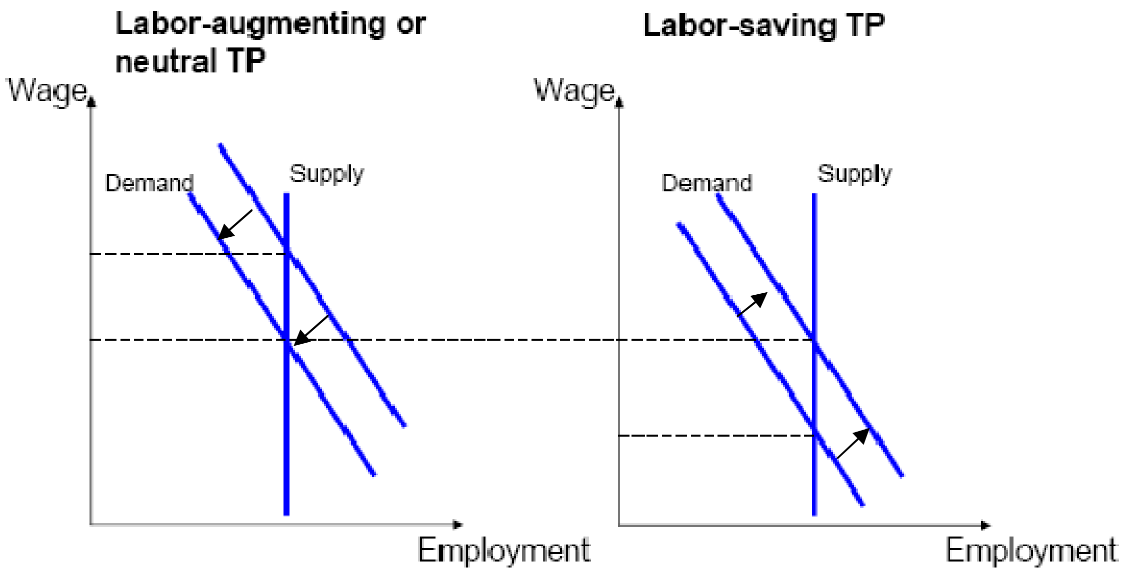
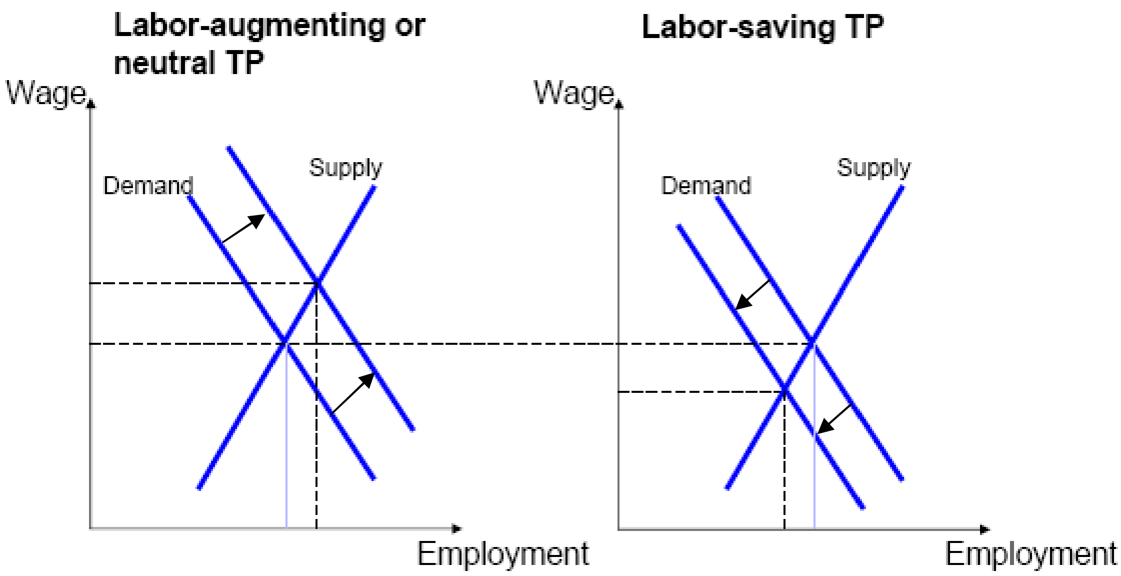


Figure I.4 analyzes the case when labor supply is elastic. On the left part of the Figure, labor augmenting or neutral technological change increases both the wage rate and the employment. On the other hand, as represented on the right part, a labor saving technical progress shrinks both employment and labor. In this case, the general effect of ICT on employment can be ambiguous, since it does not depend only on the type of technical change it represents in that particular sector, but it also depends on the elasticity of the labor supply to that sector (which can be also affected by the presence of labor unions) and on the time necessary to adjust to the different effects in the long and in the short-run. Moreover, adjustment can occur in the labor demand because of other aspects, e.g. offshoring.

Figure I.4: Theoretical effects of ICT when labor supply is elastic.



After having analyzed the data for the third stylized fact, we see that employment and ICT (both as spillover and capital accumulation) are positively correlated. In the next section we will propose an econometric model which can account for most of the stylized facts in a more detailed way. In doing so, we will expand the scope of our analysis to the sectoral level and exploit this information in order to have appropriate independent variables for our regressions. In this model we will attribute to the ICT technology the contributions arising from total factor productivity growth without attributing any portion of the capital deepening effect to a new technology since this accumulation can be replaced by non-ICT capital.

I.3 The Econometric Model and Basic the Econometric Specification

Taking the stylized facts reviewed in the previous section into account, we now examine econometric specifications which lend themselves to the analysis of the relationship between new technology and employment. An econometric analysis can be performed at different levels of aggregation. In this section, we propose a model which can provide results at the total economy level with the KLEMS dataset. We start with basic labor demand theory and then modify the use and the interpretation of some of the standard regressors usually employed in these analyses. The earliest and most widely cited studies in this area date back to Gould (1968)[26] and Hamermesh (1989)[27], who study the role of adjustment costs for labor demand in the context of a sectoral model with adjustment costs and adaptive expectations formation. Denoting respectively $ln\ N$ and $ln\ N^*$ as the logarithm of actual and desired (long-run) employment, the growth rate of employment between time t and $t-1$ is assumed proportional to the gap between actual and the desired or long-run target employment at time t and for industry i:

$$\ln N_{it} - \ln N_{it-1} = (1-\gamma)(\ln N_{it}^* - \ln N_{it}) \qquad \text{(I.2)}$$

where $0 \leq \gamma < 1$. Equation (I.2) can be rewritten adding a disturbance term μ as

$$\ln N_{it} = (1-\gamma)\ln N_{it}^* + \gamma \ln N_{it-1} + \mu_{it} \qquad \text{(I.3)}$$

In the extensive literature on labor demand, different contributions have exploited various economic models to develop an appropriate specification for estimating (I.3), and in particular N^*. Some researchers imposed rational expectations on structural models of the optimality conditions of the individual firm, but these models have met with limited success and will not be employed in the present paper.[28] Furthermore, the specifications ultimately estimated will resemble reduced forms, after an appropriate model for N^* has been substituted in (I.3). In the following sections, we present some rudimentary models for N^*.

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[26] Gould, J.P. (1968), "Adjustment Costs in the Theory of the Firm ", *Review of Economic Studies*, 35, 47-55.
[27] Hamermesh, D.S. (1989), "Labor Demand and the Structure of Adjustment Costs", *American Economic Review,* 79(4), 674-689.
[28] See for example Sargent, T.J. (1978), "Estimation of Dynamic Labor Demand Schedules under Rational Expectations."*Journal of Political Economy,* 86, 1009-44;
Burda, M.C. (1991), "Monopolistic Competition, Costs of Adjustment, and the Behavior of European Manufacturing Employment," *European Economic Review*, 35(1), 61-79; and
Pfann, G. and Palm, F. (1993), "Asymmetric Adjustment Costs in Non-linear Labour Demand Models for the Netherlands and U.K. Manufacturing Sectors," *Review of Economic Studies* 60(2), 397-412.

I.3.1 Estimation of a Labor Demand Equation with Two Production Factors

As in Bond and Van Reenen (2003)[29], we derive the labor demand equation from a static optimization problem of the firm. For our specification, we assume a constant elasticity of substitution (CES) production function with two inputs consisting of employment N_t and capital K_t. For simplicity, we suppress subscripts and write:

$$Y_t = F(K_t, N_t) = \left(\alpha_K K_t^{\rho} + \alpha_K N_t^{\rho}\right)^{\frac{1}{\rho}} \tag{I.4}$$

with $\rho = (\sigma - 1)/\sigma$, where σ is the elasticity of substitution between capital and labor. In a framework of monopolistic competition, the firm is assumed to face the following downward sloping demand curve:

$$p_t = B Y_t^{-\frac{1}{\eta^D}} \tag{I.5}$$

with B and $\eta^D > 1$ respectively representing the demand shift parameter and the price elasticity of product demand. The profit maximization problem for the firm with respect to N_t, given the constraints of technology (I.4) and demand (I.5), yields the following conditional labor demand function

$$N_t^* = \alpha_N^{\sigma} Y_t \left(\frac{w_t}{\left(1 - \frac{1}{\eta^D}\right)}\right)^{-\sigma} \tag{I.6}$$

which, after having taken the logarithms, can be written as

$$\ln N_t^* = \sigma \ln \alpha_N \left(1 - \frac{1}{\eta^D}\right) + \ln Y_t - \sigma \ln\left(\frac{w_t}{p_t}\right). \tag{I.7}$$

The last equation represents the basic form for an estimation equation. Hamermesh (1989) also adds a time trend, $tech_t$, representing the technology in the production function and arrives at the following specification:

$$\ln N_t^* = \beta_0 + \beta_1 \ln w_t + \beta_2 \ln Y_t + \beta_3 tech_t + \varepsilon_t. \tag{I.8}$$

. (I.8)

[29] Bond, S. and Van Reenen, J. (2003), "Microeconometric Models of Investment and Employment", in: J.J. Heckman and E.E. Leamer, eds., *Handbook of Econometric"*, 6, Elsevier.

I.3.2 Estimation of a Labor Demand Equation with Many Production Factors

In case of more factors of production denoted generally as x_{it}, we exploit the properties of the translog production function as in Christensen et al. (1973)[30] and apply Shephard's lemma to the conditional labor demand function to obtain

$$S_{it} = \frac{W_{it}X_{it}}{Y_t} = \alpha_i + \sum_{j-1}^{n} \beta_{ij} \ln w_{jt} + \beta_{iY} \ln Y_t + \beta_t tech_t \qquad \text{(I.9)}$$

where S_{it} is the share of factor i in total costs. The different factors can be related to different types of employees (for example, they can be differentiated by skill, gender or age groups) or capital (for example, in ICT and non-ICT).

Note that the time trend t appears once again in the last equation and represents the state of technology in the economy. Chambers (1988)[31] and Bond and Van Reenen (2003)[32] have criticized this proxy for technology for theoretical and econometric reasons; it does not take into account time-varying fluctuations in innovations, nor does it capture the embodiment of technological change in new investment. In order to refine this framework and measure the effects of ICT investment and capital on employment in a more direct way, we replace the regressor $tech_t$ with a number of alternative covariates. As we have already seen from the stylized facts, an analysis of ICT's contribution to the technological change cannot be realistically performed without considering the central role of (exogenous) total factor productivity. For these reasons, the methodology and the tools provided by growth accounting can be considered a useful starting point for detecting the role of ICT and can be complementary to the econometric analysis.

[30] Christensen L.R., Jorgenson D.W. and Lau L.J. (1973), "Transcendental logarithmic production frontiers", *Review of Economics and Statistics,* 55, 28-45.
[31] Chambers, R. (1988), "Applied Production Analysis. A Dual Approach", *Cambridge University Press.*

I.4 The Role of Total Factor Productivity in Labor Demand

In this section, we review the basics of growth accounting and use this tool to construct measures of total factor productivity. In doing so, we stress not only the limits of this methodological approach, but also its potential for studying the role of ICT-induced technological change on the demand for labor.

Estimating TFP growth: The Solow-Törnqvist Approach

The growth accounting approach studies the relationship between observable output, observable productive inputs (production factors), and total factor productivity. Assuming full efficiency, we consider the combinations of three inputs for the production function F (ICT capital, K^{ICT}, non-ICT capital, K^{NICT} , and labor service, N) and output, Y. Productivity, A, enters positively into the production function, which in turn exhibits constant returns in the three inputs

$$Y = F(A, K^{ICT}, K^{NICT}, N) \qquad \text{(I.10)}$$

Analogously to the original derivation introduced by Solow (1957)[33], and approximating in discrete time using the Törnqvist (1936) index[34], we can define total factor productivity (TFP) growth as the difference between the observable growth rate of output and a weighted average of the growth rates of the inputs:

$$\Delta \ln Y_t = \Delta \ln A_t + \bar{\alpha}_{t,NICT} \Delta \ln K_t^{NICT} + \bar{\alpha}_{t,ICT} \Delta \ln K_t^{ICT} + \bar{\alpha}_{t,N} \Delta \ln N_t \qquad \text{(I.11)}$$

The weights $\bar{\alpha}$, which are averaged over the period t and t - *1*, are elasticities of output with respect to the respective inputs, and, under perfect competition, equal to the respective income shares of the input in total value added. If we add the assumption of constant return to scale, these weights add to one: $\bar{\alpha}_{t,ICT} + \bar{\alpha}_{t,NICT} + \bar{\alpha}_{t,N} = 1$

[33] Solow, R.M. (1957), "Technical Change and the Aggregate Production Function", *Review of Economics and Statistics*, 39, 312-320.
[34] Thörnqvist, L. (1936), "The Bank of Finland's Consumption Price Index", *Bank of Finland Monthly Bulletin*, 10, 1-8.

Output Y is usually constructed from industry data. In those cases, the Solow residual should be modified using each industry's gross output relative to economy wide value added, $\omega_i = VA_i/TOT\_VA_i$ (the so-called Domar weights[35]):

$$\Delta \ln Y = \sum_i \omega_i \,\Delta \ln Y_i =$$
$$\sum_i \omega_i \, v_{i,KNICT} \Delta \ln K_{i,KNICT} + \sum_i \omega_i \, v_{i,KICT} \Delta \ln K_{i,KICT} + \sum_i \omega_i \, v_{i,SK} \Delta \ln N_{i,SK} +$$
$$\sum_i \omega_i \, v_{i,UN} \Delta \ln N_{i,UN} + \sum_i \omega_i \,\Delta \ln A_i \tag{I.12}$$

Another point worth considering is the different demand for employees N relative to hours worked H. Following Jorgenson et al. (2005)[36], average labor and capital productivity are defined as $y = Y/H$ and $k = K/H$ and equation (I.12) can be rewritten as

$$\Delta \ln y = \sum_i \omega_i \,(\Delta \ln Y_i - \Delta \ln H_i) = \sum_i \omega_i \, v_{i,KNICT} \Delta \ln k_{i,KNICT} + \sum_i \omega_i \, v_{i,KICT} \Delta \ln k_{i,KICT} +$$
$$\sum_i \omega_i \, v_i (\Delta \ln N_i - \Delta \ln H_i) + \sum_i \omega_i \,\Delta \ln A_i \tag{I.13}$$

where $(\Delta lnN - \Delta lnH)$ is defined as labor quality.

Beyond Growth Accounting: Problems with TFP indicators

The information contained in the growth accounting framework above cannot be exploited directly for labor demand estimation for the following reasons:

1. Endogeneity makes it difficult to derive a consistently estimable econometric specification in which the dependent variable is employment.
2. The value of K^{ICT} is often difficult to measure especially when the time series are relatively short.
3. The simple Solow decomposition reveals little or nothing about factor complementarity, especially of the capital-skill type relevant for ICT.

On the other hand, following Jalava and Pohjola (2007)[37] and considering the structure of the growth accounting approach, ICT affects output through three channels:

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[35] Domar, E.D. (1961), "On the Measurement of Technological Change", *Economic Journal* 71, no. 824, 709-29.
[36] Jorgenson, D.W., Ho, M. and Stiroh, K.J. (2005), "Information Technology and the American Growth Resurgence", *The MIT Press.*
[37] Jalava, J. and Pohjola, M. (2007), "The Roles of Electricity and ICT in Economic Growth: Case Finland", *Explorations in Economic History,* 45(3), 270-287.

1. via TFP growth, ΔlnA_t;
2. via ICT capital deepening;
3. via ICT spillovers from the ICT producer industries.

This taxonomy of influences suggests that ICT's effects should be divided into capital deepening and productivity spillovers originating from the new technologies in the total economy. In the next section, we will proceed along these lines and describe several approaches which are most often used in the growth and microeconometrics literature. The ICT spillover can be represented as

1. a deterministic trend with a structural break after 1995;
2. the ratio I_{ICT}/Y;
3. ICT TFP growth defined from social accounting, the dual approach or from a macroeconomic model.

I.5 Proxying for TFP Growth and ICT Spillovers in Labor Demand

I.5.1 Technological Change as Structural Break after 1995

An important issue to resolve is how to model the evolution of technical change, $tech_t$

We could proxy for the level shifts by multiplying the time trend $tech_t$by a dummy taking the value 1 after some year in which some structural break occurred. In the literature there is empirical evidence that 1995 was such a watershed structural break year for the US, especially in light of Stiroh (2002)[38]'s findings. Moreover, in a recent contribution Dahl et al. (2007)[39] find similar evidence for European countries. Even if this method does capture the structural break observed in 1995 and it is easy to construct, it will not capture other smaller yet important new innovations in ICT goods introduced before and after 1995.

I.5.2 Technology as Ratio I_{ICT} / Y

Following fundamental contributions by Zvi Griliches on the relationship between R&D expenditures and productivity, some researchers have approximated technological change using the ratio of research and development expenditures to GDP ($R\&D/Y$). [40] Following the same procedure, we can use the ratio of ICT investment to GDP (I_{ICT}/Y) as a proxy of the technological progress in an economy. This approach presents several benefits: first of all, we consider a direct measure for the ICT penetration in our specification; secondly, this measure is better than the R&D measure, since most of the firms are investing in ICT technologies; thirdly, the necessary data are available in the EU KLEMS dataset. As drawbacks, I_{ICT}/Y is also a choice variable, potentially creating endogeneity problems. In Section 8 we will address this issue in more detail.

I.5.3 Technology as ICT TFP Growth

One alternative approach is to employ ICT-related TFP directly as a proxy for technology. ICT TFP can be defined as the share of technological change attributable to ICT spillovers; this definition can be used in our regression in order to detect the effect of ICT which is not related to ICT capital accumulation. Several suggestions can be found in the literature for constructing this measure.

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[38] Stiroh, K.J. (2002), "Information Technology and the US Productivity Revival: What Do the Industry Data Say?", *The American Economic Review*, 92(5), 1559-1576.
[39] Dahl, C.M., Kongsted C.H. and Sørensen, A. (2007), "ICT and Productivity Growth: The Timing of Structural Breaks in Productivity Growth and the Link to Information Technology", Paper presented at the 4th EUKLEMS Consortium Meeting, Brussel, March.
[40] Several of Zvi Griliches' essays on this topic can be found in Griliches, Z. (1999), "R&D and Productivity: The Economic Evidence", *NBER Monograph*, University of Chicago Press.

One method used frequently in the economic history literature can be found using the so-called social accounting methodology. Crafts (2004)[41], expanding upon an idea introduced by Fogel (1964)[42], studies the positive spillover effects created by American railroads and industrial revolutions on the US American and English economy. Jalava and Pohjola (2008)[43] apply this reasoning to the case of ICT. In this case, the analysis is based on the Solow residual and consists of separating the direct contribution of ICT production as spillover from the indirect impact on output through the increase in the investment growth. Assuming constant returns to scale and the fact that in the long-run output and capital grow at the same rate, $\Delta lnY = \Delta lnK$, equation (I.11) can be rewritten as

$$\Delta lnY = \Delta lnN + \frac{\Delta lnA}{(1-\alpha_{k})} \qquad \text{(I.14)}$$

Following them, one would proxy productivity in a counterfactual world without ICT, ΔlnA_{NICT}^{C}, by first constructing aggregate Solow residuals in traditional manufacturing industries and then calculating ICT TFP as

$$\Delta A_{ICT} = \frac{\Delta A - \Delta A_{NICT}^{C}}{(1-\alpha_{K})} \qquad \text{(I.15)}$$

In the same spirit, Jorgenson et al. (2005)[44] suggest estimating the ICT TFP contribution by exploiting the price or "dual" approach, where TFP growth is defined as the decline in the price of output plus a weighted average of the growth rates of input prices with value shares of inputs as weights. Moreover, using Jorgenson et al. (1987)'s methodology, they study the aggregate economy and, exploiting the Domar weights, identify the ICT TFP contribution considering the ratio of TFP of the ICT producer industries related to the total economy.[45]
Stiroh (2002) employs an econometric approach and considers the industry panel structure explicitly, estimating the ICT TFP contribution through the parameter β in the following regression equation:[46]

[41] Crafts, N. (2004), "Social Savings as a Measure of the Contribution of a New Technology to Economic Growth", *Working Paper No. 06/2004,* Department of Economic History, London School of Economics.
[42] Fogel, R.W. (1964), "Railroads and American Economic Growth: Essays in Econometric History", *John Hopkins University Press,* Baltimore.
[43] Jalava, J. and Pohjola, M. (2007), "The Roles of Electricity and ICT in Economic Growth: Case Finland", *Explorations in Economic History,* 45(3), 270-287.
[44] Jorgenson, D.W., Ho, M. and Stiroh, K.J. (2005), "Information Technology and the American Growth Resurgence", *The MIT Press.*
[45] Jorgenson, D.W., Gollop, F. and Fraumeni, B. (1987), "Productivity and US Economic Growth", *Harvard University Press.*
[46] Stiroh, K.J. (2002), "Are ICT Spillovers driving the New Economy?", *Review of Income and Wealth,* 48(1), 33-57.

$$\Delta A_{i,t} = \beta \Delta lnKICT_{i,t} + \lambda_{i,t} + u_{i,t} \tag{I.16}$$

Where the subscripts i and t respectively denote industry and time and λ is a dummy.

Finally, Greenwood et al. (1997)[47] exploit the long-run first order conditions of a neoclassical model and measure the contribution of ICT investment to total TFP as

$$\Delta A_{ICT} = \frac{\alpha^{KICT}(1/\Delta p_{KICT})}{\Delta A + \alpha^{KICT}(1/\Delta p_{KICT})}. \tag{I.17}$$

This expression is useful since it provides the fraction of long-run growth that would remain if all the neutral technological change is equalized to 0, i.e. $\Delta A = 0$, the fraction of long-run growth due to investment-specific technological change.

A problem arises when capital prices are not available, as in the public version of the EU KLEMS dataset. However, as suggested in the EU KLEMS manual, it is possible to construct values using an arbitrage equation from neo-classical investment theory as proposed by Jorgenson (1963)[48] and Jorgenson and Griliches (1967)[49]. This equation assumes that in equilibrium, an investor is indifferent between two alternatives: buying a unit of capital at investment price p^I_{kt}, and adding the rental price and then obtaining $(1-\delta_k)p^I_{kt+1}$ by selling the depreciated asset in the next period or earning the nominal rate of return i_t. Without taxation, the rental fee is then determined by the nominal rate of economic depreciation and the asset specific capital gains, i.e.

$$p^K_{k,t} = p^I_{k,t-1}i_t + \delta_k p^I_{k,t} - [p^I_{k,t} - p^I_{k,t-1}] \tag{I.18}$$

or

$$p^K_{k,t} = r_{k,t}p^I_{k,t-1} + \delta_k p^I_{k,t} \tag{I.19}$$

While the depreciation rate δ_k, is assumed to be constant over time for each country provided by EU KLEMS, the nominal rate of return can be estimated either by using the interest rates on

[47] Greenwood, J., Hercowitz, Z. and Krusell, P. (1997), "Long-Run Implications of Investment-Specific Technological Change", *American Economic Review*, vol. 87(3), 342-62. See also the discussion in Greenwood, J. and Krusell, P. (2007), "Growth Accounting with Investment-Specific Technological Progress: A Discussion of Two Approaches", *Journal of Monetary Economic,* 54(4), 1300-1310; and Oulton, N. (2007), "Investment-Specific Technological Progress and Growth Accounting", *Journal of Monetary Economics,* 54(4), 1290-1299.

[48] Jorgenson, D.W. (1963), "Capital Theory and Investment Behaviour", *American Economic Review*, 53(2), 247-259.

[49] Jorgenson, D.W. and Griliches, Z. (1967), "The Explanation of Productivity Change", *Review of Economic Studies,* 34, 249-83.

government bonds or by using the ex-post approach, which estimates the residual given the value of capital compensation from the national accounts, depreciation and the capital gains. So we compute for $r_{k,t}$ an internal rate of return which can vary across industries, i.e.

$$i_{j,t} = \frac{p^K_{j,t}K_{j,t} + \sum_k [p^I_{k,j,t} - p^I_{k,j,t-1}]A_{k,j,t} - \sum_k p^I_{k,j,t}\delta_k A_{k,j,t}}{\sum_k p^I_{k,j,t-1}A_{k,j,t}} \qquad \text{(I.20)}$$

where $p^K{}_{j,t}K_{j,t}$ is the capital compensation in industry j and $A_{k,j,t}$ is the asset representing capital. The neglect of taxation is an important limitation of the analysis but, given the sluggish behavior of marginal tax rates, probably not a first-order source of variation in the data.

I.6 Data

I.6.1 The EU KLEMS Dataset

The central dataset in the implementation of the labor demand estimation that we propose is the EU KLEMS dataset (see van Ark et al., 2008). We employ the following variables presented in Table I.12 for the industries shown in Table I.13:

Table I.12: EU KLEMS variables used for the regressions

Variable and Definition	*EU KLEMS Variable Names*	*Description*
employment N	*EMPE*	*Number of employees (thousands)*
wage $w = \frac{COMP}{N}$	*COMP*	*Labor compensation (in millions of local currency)*
Gross value added at constant prices (output) Y	*VA*	*Gross value added (price adjusted)*
ICT Investment I_{ICT}	*Iq_ICT*	*Real gross fixed capital formation, 1995 prices CT, IT, and Software*
Productivity level A	*TFPva_I*	*TFP (value added based) growth, 1995=100*

Table I.13: EU-KLEMS industries used in the econometric analysis (in bold)

Description	*EU KLEMS Code*
TOTAL INDUSTRIES	**TOT**
AGRICULTURE, HUNTING, FORESTRY AND FISHING	**AtB**
AGRICULTURE, HUNTING AND FORESTRY	A
Agriculture	1
Forestry	2
FISHING	B
MINING AND QUARRYING	**C**
MINING AND QUARRYING OF ENERGY PRODUCING MATERIALS	10t12
Mining of coal and lignite; extraction of peat	10
Extraction of crude petroleum and natural gas and services	11
Mining of uranium and thorium ores	12
MINING AND QUARRYING EXCEPT ENERGY PRODUCING MATERIALS	13t14
Mining of metal ores	13
Other mining and quarrying	14
TOTAL MANUFACTURING	D
FOOD , BEVERAGES AND TOBACCO	**15t16**
Food and beverages	15
Tobacco	16
TEXTILES, TEXTILE , LEATHER AND FOOTWEAR	**17t19**
Textiles and textile	17t18
Textiles	17
Wearing Apparel, Dressing And Dying Of Fur	18
Leather, leather and footwear	19
WOOD AND OF WOOD AND CORK	**20**
PULP, PAPER, PAPER , PRINTING AND PUBLISHING	**21t22**
Pulp, paper and paper	21
Printing, publishing and reproduction	22
Publishing	221
Printing and reproduction	22x
CHEMICAL, RUBBER, PLASTICS AND FUEL	23t25
Coke, refined petroleum and nuclear fuel	**23**
Chemicals and chemical products	**24**
Pharmaceuticals	244
Chemicals excluding pharmaceuticals	24x
Rubber and plastics	**25**
OTHER NON-METALLIC MINERAL	**26**
BASIC METALS AND FABRICATED METAL	**27t28**
Basic metals	27
Fabricated metal	28
MACHINERY, NEC	**29**
ELECTRICAL AND OPTICAL EQUIPMENT	**30t33**
Office, accounting and computing machinery	30
Electrical engineering	31t32
Electrical machinery and apparatus, nec	31
Insulated wire	313
Other electrical machinery and apparatus nec	31x
Radio, television and communication equipment	32
Electronic valves and tubes	321

Telecommunication equipment	322
Radio and television receivers	323
Medical, precision and optical instruments	33
Scientific instruments	331t3
Other instruments	334t5
TRANSPORT EQUIPMENT	**34t35**
Motor vehicles, trailers and semi-trailers	34
Other transport equipment	35
Building and repairing of ships and boats	351
Aircraft and spacecraft	353
Railroad equipment and transport equipment nec	35x
MANUFACTURING NEC; RECYCLING	**36t37**
Manufacturing nec	36
Recycling	37
ELECTRICITY, GAS AND WATER SUPPLY	**E**
ELECTRICITY AND GAS	40
Electricity supply	40x
Gas supply	402
WATER SUPPLY	41
CONSTRUCTION	**F**
WHOLESALE AND RETAIL TRADE	G
Sale, maintenance and repair of motor vehicles and motorcycles; retail sale of fuel	**50**
Wholesale trade and commission trade, except of motor vehicles and motorcycles	**51**
Retail trade, except of motor vehicles and motorcycles; repair of household goods	52
HOTELS AND RESTAURANTS	**H**
TRANSPORT AND STORAGE AND COMMUNICATION	**I**
TRANSPORT AND STORAGE	60t63
Other Inland transport	60
Other Water transport	61
Other Air transport	62
Other Supporting and auxiliary transport activities; activities of travel agencies	63
POST AND TELECOMMUNICATIONS	**64**
FINANCE, INSURANCE, REAL ESTATE AND BUSINESS SERVICES	**JtK**
FINANCIAL INTERMEDIATION	J
Financial intermediation, except insurance and pension funding	65
Insurance and pension funding, except compulsory social security	66
Activities related to financial intermediation	67
REAL ESTATE, RENTING AND BUSINESS ACTIVITIES	K
Real estate activities	70
Renting of m&eq and other business activities	71t74
Renting of machinery and equipment	71
Computer and related activities	72
Research and development	73
Other business activities	74
Legal, technical and advertising	741t4
Other business activities, nec	745t8
COMMUNITY SOCIAL AND PERSONAL SERVICES	LtQ
PUBLIC ADMIN AND DEFENCE; COMPULSORY SOCIAL SECURITY	L
EDUCATION	M
HEALTH AND SOCIAL WORK	N

OTHER COMMUNITY, SOCIAL AND PERSONAL SERVICES	O
Sewage and refuse disposal, sanitation and similar activities	90
Activities of membership organizations nec	91
Recreational, cultural and sporting activities	92
Media activities	921t2
Other recreational activites	923t7
Other service activities	93
PRIVATE HOUSEHOLDS WITH EMPLOYED PERSONS	P
EXTRA-TERRITORIAL ORGANIZATIONS AND BODIES	Q

I.6.2 The OECD Product Market Regulation Dataset

For measuring product market regulations, we consider the OECD Indicators of Regulation Impact constructed by Conway and Nicoletti (2006)[50] which measure the potential costs of anti-competitive regulation in selected non-manufacturing sectors (especially related to energy and services industries) on sectors of the economy that use the output of non-manufacturing sectors as intermediate inputs in the production process.

I.6.3 The Fondazione Rodolfo Debenedetti Social Reform Database

In order to study the different policies related to the European labor market, we consider two different databases: the OECD EPL series and the Fondazione Rodolfo Debenedetti database. The OECD EPL is given by the summary indicator of the stringency of Employment Protection Legislation[51]. Differently, the Fondazione Rodolfo Debenedetti database collects information about social reforms in the EU15 Countries (except Luxembourg) over the period 1987-2005. The database is focused on four areas of reforms:

- Employment Protection Legislation (EPL);
- Public Pension Systems (PEN);
- Non-Employment Benefits (NEB);
- Migration Policies (IMM).

The aim of the fRDB Social Reforms Database is to collect *qualitative* features of reforms. Reforms have been classified along two main dimensions: **direction** (i.e. reduction or increase of the generosity) and **scope** (i.e. marginal or radical). In particular, in order to decide whether a reform is marginal or radical, a two step procedure is implemented: first a qualitative assessment on the reforms is made and then trends in selected time series are analyzed.

[50] Conway, P. and Nicoletti, G. (2006), "Product Market Regulation in the Non-Manufacturing Sectors of OECD Countries: Measurement and Highlights", *OECD Economics Department Working Paper*, No 530.
[51] OECD (2004), "Employment Outlook 2004", OECD.

I.7 Econometric Specification and Results for Germany and the United States

In this section we present a battery of estimation results for Germany and the United States. In the Annex we present results for all the EU countries for which there are adequate data.

I.7.1 Results from the benchmark estimating equation

We estimate the labor demand equation in two steps: the first gives the prediction or target long-run labor demand in sector i at time t:

$$\ln N_{it}^{*} = \beta_0 + \beta_1 \ln w_{it} + \beta_2 \ln Y_{it} + \beta_3 tech_t + \varepsilon_{it} \tag{I.21}$$

while the second step specifies the corresponding level of employment which is realized:

$$\ln N_{it} = (1-\gamma)\ln N_{it}^{*} + \gamma \ln N_{it-1} + \mu_{it} \tag{I.22}$$

The choice of an appropriate specification is important and may influence the final results. In Table I.14 we present estimation results from two different strategies for implementing the standard specification of labor demand following Hamermesh (1993)[52] using US data, in which long-run employment is expressed as a function of wages, output and a time trend: the fixed effect, the clustering and the weighted least square (WLS) estimation technique. In this report we will concentrate primarily on the long-run labor demand equation and provide estimates of (I.21).

The panel structure represents the standard estimation approach for the analysis of labor demand and allows us to consider a fixed effect for each industry: the first column of Table I.14 shows that, as implied by the theory of labor demand, wage and output are both significant and have a negative and positive effect on the total number of employees demanded, respectively. Technology, modeled here as a linear trend, has a negative and significant impact on labor demand suggesting that the new innovations have a labor saving effect on this economy.

Even if this technique is widely used in the literature, we follow Kloek (1981)[53] in column (2) and implement a cluster-specific random effect model, where clusters - assumed to be independent across groups - are observations which come from the same industry. Moreover, as suggested by Feenstra and Hanson (2003)[54], we assume that the errors are independent and

[52] Hamermesh, D.S. (1993), "Labor Demand", Princeton University Press, Princeton, New Jersey.
[53] Kloek, T. (1981), "OLS Estimation in a Model where a Microvariable is Explained by Aggregates and Contemporaneous Disturbances are Equicorrelated", *Econometrica*, 49, 1-19.
[54] Feenstra, R.C. and Hanson, G.H. (2003), "Global Production Sharing and Rising Inequality: A Survey of Trade and Wages", in Choi, E.K. and Harrigan, J. eds., "*Handbook of International Trade*", Oxford: Blackwell.

heteroskedastic satisfying $E(\varepsilon_{it}) = 0$ and $Var(\varepsilon_{it}) = \sigma^2/\omega_i$, where w_i are represented by exogenous values which sum to one, i.e. $\sum_{i=1}^{N} \omega_i$. In this way, we correct the previous estimation by taking first the differences and then computing a WLS estimation constructing the shares as

$$\omega_{it} = \frac{1}{2}\left(\frac{VA_{it-1}}{\sum_{i=1}^{N} VA_{it-1}} + \frac{VA_{it}}{\sum_{i=1}^{N} VA_{it}}\right) \tag{I.23}$$

i.e. the average of the ratios of the value added of industry j to the value added of the total economy at time t and $t - 1$ and the weights $\sqrt{w_i}$. We will apply the last method for all the other estimations in this section since it takes into account the random component of the model and the different sectoral sizes.

Once we have applied the cluster-specific random effect model and implemented the WLS, we introduce the difference of the square of time in order to catch any effect of technology when first differences are employed. Table I.14 shows two different specifications: columns (1) and (2) respectively display the level and the difference specification. In this case, only the output sign remains consistent with the previous regression.

Table I.14: Labor demand estimate, US economy, levels and difference specifications

USA Dependent Variable: Employment		
	ln N(1) β/s.e.	Δ ln N(2) β/s.e.
ln w	-0.47***	
	(0.05)	
ln Y	0.77***	
	(0.02)	
T	-0.01***	
	(0.00)	
Δ ln w		3.04*
		(1.48)
Δ ln Y		0.49***
		(0.05)
Δ t^2		0.02***
		(0.00)
Constant	20.12***	4.69***
	(3.94)	(1.07)
N obs	725	700
R^2	0.59	0.72
N ind	25	25

***, **, *: statistically significant at 1, 5, and 10 % level, respectively; robust standard errors in parentheses

I.7.2 Estimates of Augmented Conditional Labor Demand Estimates for Germany and the US

In this section, we present weighted least squares (WLS) estimates of the augmented conditional labor demand specification (I.21) which are estimated separately on panels of industry data from the US and Germany. Table I.15 presents our regression results for US total employment in first-differenced form. The data covers all the 700 observations available for the period 1970-2005 and for the industries considered in Table I.13. The dependent variable is represented by ΔlnN, while the explanatory variables are divided into two different groups. The first two rows with Δlnw and ΔlnY correspond to the standard variables used by Hamermesh, while the other group contains different specifications for the technology variable.

Column (1) presents results of the second regression reported in Table I.14, where the technological change is proxied by the difference in the square of time ($\Delta\, t^2$), i.e. a linear trend. Column (2) employs a dummy variable taking on a value of 1 after 1995 ($Dummy_{1995}$). In column (3), technology is proxied as the ratio of ICT investment to output ($\Delta\, I_{ICT}/Y$). Column (4) applies equation (I.15) from the social accounting approach (ICT_TFPG_{SOC},) while in the regressions reported in columns (5) and (6) the “dual approach” methodology applied by Jorgenson et al. (2005) (ICT_TFPG_{JOR}) and by Greenwood et al. (1997) (ICT_TFPG_{GHK}) is used. Since the ICT investment series are not complete in the EU KLEMS dataset, we employ total factor productivity growth calculated as the standard Solow residual. In this case, the growth in technology has a positive and significant effect when we treat technology as an exponential trend, a dummy post 1995 or when the ICT TFP growth is used. Moreover, for the first group we can observe that only output has a robust effect on labor demand with a positive and strongly significant coefficient, while the sign of the coefficient on wages is not negative or significant in most of the cases, except for the last specification in which we control for regulation (see column 7). In this case, we can only control for product market regulation ($\Delta\, RC$) since the OECD EPL indicator ($\Delta\, EPL$) does show any change regarding the labor market regulation in the US. The estimation results suggest that the regulatory environment in product markets is indeed important and may diminish the growth rate of employment.

Table I.15: Labor demand estimates, US economy, different specifications

	USA Dependent Variable: $\Delta \ln N$						
	(1) β/s.e.	(2) β/s.e.	(3) β/s.e.	(4) β/s.e.	(5) β/s.e.	(6) β/s.e.	(7) β/s.e.
$\Delta \ln w$	3.04*	0.08	-1.79	-1.77	-1.74	-1.79	5.36***
	(1.48)	(1.23)	(1.14)	(1.13)	(1.18)	(1.13)	(1.11)
$\Delta \ln Y$	0.49***	0.48***	0.46***	0.46***	0.46***	0.53***	0.46***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.08)	(0.11)
Δt^2	0.002***						
	(0.00)						
$Dummy_{1995}$		0.51***					
		(0.10)					
$\Delta I_{ICT}/Y$			4.24				
			(3.61)				
ICT_TFPG_{SOC}				0.04			
				(0.04)			
ICT_TFPG_{JOR}					34.73***		31.60***
					(5.37)		(4.98)
ICT_TFPG_{GHK}						1.59	
						(1.22)	
ΔRC							-3.26*
							(1.77)
Constant	4.69***	5.31***	5.24***	5.26***	5.19***	6.58***	5.45*
	(1.07)	(1.16)	(1.16)	(1.16)	(1.15)	(1.62)	(2.35)
N obs	700	700	700	700	700	700	364
R^2	0.72	0.69	0.65	0.65	0.66	0.66	0.51
N ind	25	25	25	25	25	25	14

***, **, *: statistically significant at 1, 5, and 10 % level, respectively; robust standard errors in parentheses.

Legend:

- $\Delta(I_{ICT}/Y)$ is the change in the investment rate in ICT expressed as a fraction of value added
- ICT_TFPGSOC is the ICT TFP derived from the social accounting approach ICT_TFPGJOR is the ICT TFP derived from the dual approach
- ICT_TFPGGHK is the ICT TFP derived from Greenwood et al. (1997) approach
- Δ RC is the control for the product market regulation

Table I.16 represents the same specification except for the dependent variable: we replace employment with *labor quality*: in this case, while for the technology definitions the sign and the significance are the same as in the previous table, we can see that now wages are important in explaining the level of labor quality.

Table I.16: Labor quality estimates, US economy, different specifications

	USA Dependent Variable: Δ ln *(N/H)*						
	(1) β/s.e.	(2) β/s.e.	(3) β/s.e.	(4) β/s.e.	(5) β/s.e.	(6) β/s.e.	(7) β/s.e.
Δ ln *w*	1.32*	-2.02***	-4.27***	-4.26***	-4.21***	-4.28***	-5.07***
	(0.78)	(0.97)	(1.00)	(1.00)	(1.08)	(0.94)	(0.87)
Δ ln *Y*	0.05*	0.04*	0.02	0.02	0.02	0.06	-0.04
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.04)	(0.5)
Δ t^2	0.02***						
	(0.00)						
$Dummy_{1995}$		0.61***					
		(0.04)					
Δ I_{ICT}/Y			5.91				
			(3.75)				
ICT_TFPG_{SOC}				0.03			
				(0.04)			
ICT_TFPG_{JOR}					43.09***		28.63***
					(3.29)		(4.34)
ICT_TFPG_{GHK}						1.02	
						(0.77)	
Δ *RC*							-2.42
							(1.56)
Constant	3.45***	4.17***	4.08***	4.12***	4.02***	4.96***	2.90*
	(0.44)	(0.45)	(0.47)	(0.46)	(0.46)	(0.78)	(1.09)
N obs	700	700	700	700	700	700	364
R^2	0.60	0.41	0.07	0.07	0.13	0.09	0.22
N ind	25	25	25	25	25	25	14

***, **, *: statistically significant at 1, 5, and 10 % level, respectively; robust standard errors in parentheses.
Legend:

- Δ(I_{ICT}/Y) is the change in the investment rate in ICT expressed as a fraction of value added
- ICT_TFPGSOC is the ICT TFP derived from the social accounting approach ICT_TFPGJOR is the ICT TFP derived from the dual approach
- ICT_TFPGGHK is the ICT TFP derived from Greenwood et al. (1997) approach
  Δ RC is the change in the product market regulation

Tables I.17 (where the dependent variable is represented by employment) and I.18 (where the dependent variable is labor quality) display the same regressions as in Tables I.15 and I.16 but for Germany only. In this case we can also control for employment protection legislation, since this type of data is available for some European countries. Similar to the US, in Table I.17 we can observe that wage and output play an important role in the specifications respectively entering with a negative and positive sign. Moreover, even if it is often not significant, technology enters with a positive sign. A different picture appears when labor quality is considered: in these regressions, technology seems to be the main driver in increasing the ratio between employment and hours worked.

Table I.17: Labor demand estimates, German economy, different specifications

	Germany Dependent Variable: $\Delta \ln N$								
	(1) β/s.e.	(2) β/s.e.	(3) β/s.e.	(4) β/s.e.	(5) β/s.e.	(6) β/s.e.	(7) β/s.e.	(8) β/s.e.	(9) β/s.e.
$\Delta \ln w$	-0.32	-4.80***	0.10	-7.24***	-7.25***	0.09	-5.39***	0.34	-1.92**
	(0.80)	(0.51)	(0.83)	(1.25)	(1.26)	(0.90)	(0.79)	(0.86)	(0.52)
$\Delta \ln Y$	0.36***	0.36***	0.42***	0.35***	0.35***	0.53***	0.52***	0.41***	0.52***
	(0.06)	(0.06)	(0.04)	(0.06)	(0.06)	(0.07)	(0.09)	(0.04)	(0.09)
Δt^2	0.02***								
	(0.01)								
$Dummy_{1995}$		0.35							
		(0.19)							
$\Delta I_{ICT}/Y$			2.92						
			(4.64)						
ICT_TFPG_{SOC}				0.00					
				(0.00)					
ICT_TFPG_{JOR}					18.02*		20.33**	5.21	9.71**
					(8.75)		(4.94)	(5.40)	(2.83)
ICT_TFPG_{GHK}						2.55*			
						(1.13)			
ΔRC							1.98		0.10
							(1.97)		(2.25)
ΔEPL								-0.08*	0.03
								(0.04)	(0.02)
Constant	2.68*	3.36**	4.88***	3.49*	3.46*	7.06***	6.57*	4.73**	6.86**
	(0.98)	(1.18)	(0.85)	(1.28)	(1.26)	(1.35)	(1.76)	(0.85)	(1.73)
N obs	875	875	350	875	875	350	392	325	168
R^2	0.65	0.58	0.77	0.56	0.56	0.80	0.59	0.77	0.71
N ind	25	25	14	25	25	14	14	14	14

***, **, *: statistically significant at 1, 5, and 10 % level, respectively; robust standard errors in parentheses.

Legend:

- $\Delta(I_{ICT}/Y)$ is the change in the investment rate in ICT expressed as a fraction of value added
- ICT_TFPGSOC is the ICT TFP derived from the social accounting approach ICT_TFPGJOR is the ICT TFP derived from the dual approach
- ICT_TFPGGHK is the ICT TFP derived from Greenwood et al. (1997) approach

  Δ RC is the control for the product market regulation

  ΔEPL is the change in the labor market regulation

Table I.18: Labor quality estimates, German economy, different specifications

	Germany Dependent Variable: $\Delta \ln (N/H)$								
	(1) β/s.e.	(2) β/s.e.	(3) β/s.e.	(4) β/s.e.	(5) β/s.e.	(6) β/s.e.	(7) β/s.e.	(8) β/s.e.	(9) β/s.e.
$\Delta \ln w$	0.23	-4.60***	0.06	-7.68***	-7.69***	0.06	-3.92***	0.25	-0.51**
	(0.46)	(0.52)	(0.42)	(0.45)	(0.46)	(0.40)	(0.71)	(0.42)	(0.27)
$\Delta \ln Y$	0.04*	0.04*	0.05**	0.03	0.03	0.08*	0.00	0.05**	0.00
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.01)	(0.04)
Δt^2	0.02***								
	(0.01)								
$Dummy_{1995}$		0.45***							
		(0.06)							
$\Delta I_{ICT}/Y$			0.95						
			(2.28)						
ICT_TFPG_{SOC}				0.00					
				(0.00)					
ICT_TFPG_{JOR}					22.34***		16.78**	6.89***	6.17**
					(4.17)		(4.36)	(1.07)	(2.02)
ICT_TFPG_{GHK}						0.59			
						(0.56)			
ΔRC							0.85		-2.03
							(0.93)		(1.15)
ΔEPL								-0.02	-0.02
								(0.02)	(0.03)
Constant	3.08***	3.84***	4.58***	4.00*	3.97***	5.08***	3.30***	4.53***	3.58***
	(0.29)	(0.35)	(0.35)	(0.40)	(0.39)	(0.63)	(0.62)	(0.34)	(0.76)
N obs	875	875	350	875	875	350	392	325	168
R^2	0.74	0.48	0.16	0.35	0.36	0.17	0.11	0.16	0.03
N ind	25	25	14	25	25	25	14	14	14

***, **, *: statistically significant at 1, 5, and 10 % level, respectively; robust standard errors in parentheses

I.8 Econometric Caveats

A number of caveats regarding our econometric analysis should be made since, when this type of regressions is performed, problems related to endogeneity, measurement errors and cointegration may arise and may require careful attention.

I.8.1 Endogeneity and the Role of Wage-Setting and other Labor Market Institutions

As we have already noted in Section 5, the choice of the ratio I^{ICT}/Y as a measure of technological change may lead to an endogeneity problem, since the ratio can be considered a choice variable of the firm. Also the variable wage can create problems since it is assumed to move together with the economy.[55]

One concrete way labor market institutions can affect the endogeneity of the wage is illustrated by a simple model following Acemoglu (2003) represented by Figure I.5, which depicts the relation between the skill premium, $\overline{\omega}$, and the employment structure proxied by the skilled to unskilled employment ratio (S/U).[56] The wage is given on the vertical axis and the amount of employment demand on the horizontal one. A represents the point of equilibrium for the EU and the US at time t. Now let us assume that the relative supply of skills is fixed, or at least relatively inelastic, and technological change (or international trade) increases the relative demand of skills: if like in the US there exists no particular wage institutions, the new equilibrium point will be represented by point B, in which the skill premium increases. However, in countries where an institutional wage setting is present, the new equilibrium is in point C, where the wage premium is not changed, but the ratio $Skilled/Unskilled$ increases creating unemployment in the economy.

[55] See Section II.5.4.3 for more details on this issue.
[56] Acemoglu, D. (2003), “Cross Country Inequality Trends”, *Economic Journal*, 113, 121-149.

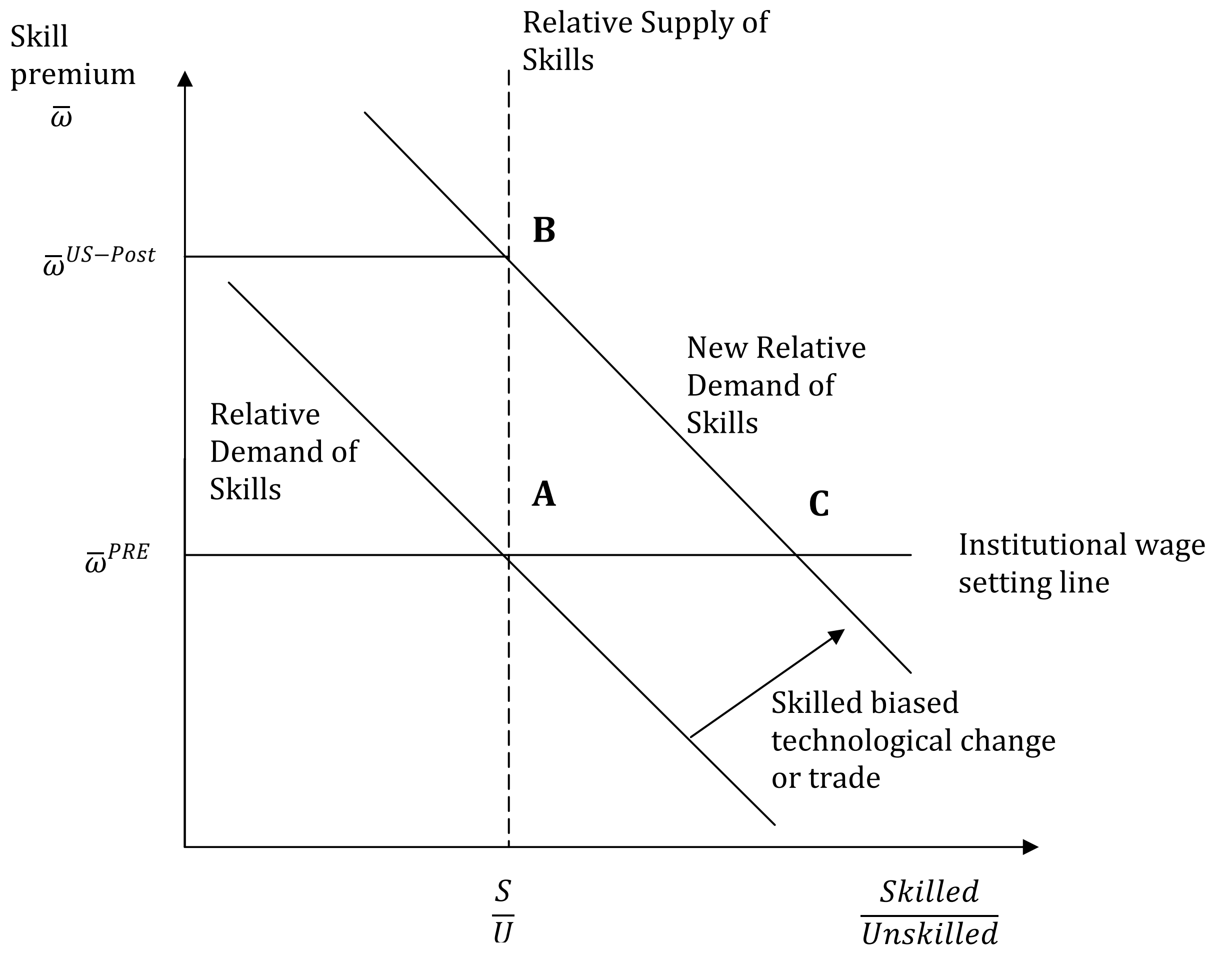

Figure I.5: Labor demand, technology and institutional wage setting

I.8.2 Cointegration

Another problem can arise with non-stationary data. In the event that our data are characterized by stochastic trends, the level regressions will yield inconsistent estimates. In this subsection we estimate both the long- and short-term forces in a single statistical model exploiting the properties of the error correction model (ECM). Equation (I.22) already implies that the dependent variable employment is characterized by a certain order of integration. The series has a permanent memory such that past shocks to the series cumulate. Moreover, growth accounting shows that the time series labor, output and total factor productivity are likely to never drift too far apart from each other i.e. they seem to share a common long-run equilibrium relation. For these reasons we consider the single-equation error correction model

$$\Delta lnN_t = \alpha_0 + \alpha_1(lnN_{t-1} - \beta_1 lnX_{t-1}) + \alpha_2 \Delta lnX_{t-1} + \gamma_t \qquad \text{(I.24)}$$

Equation (I.24) presents the current changes in employment $\Delta ln\, N_t$ as a function of the first difference of current changes of the explanatory variables represented by $\Delta ln\, X_t$. More precisely, β_0 represents the contemporaneous or short-run effect that the vector ΔlnX has on employment. Differently, the coefficient α_2 captures the causal effect which occurs in equilibrium of $ln\, X$ on $ln\, N$. Finally, the coefficient α_1 represents the rate at which the variables return to their long-run relationship.

I.8.3 First Stage of the Error Correction Model: The Long-run Regression

Using the same approach as the one described in I.7.1, we study the effects in equilibrium of the explanatory variables on the level of employment. As the first stage of our error correction model we propose two specifications in which the explanatory variables consist of a constant, the logarithm of wage $ln\, w$, the logarithm of output, $ln\, Y$ and the square of time t^2 representing technological change. The first specification does not impose any constraints while in the second one we require the output elasticity to be equal to 1. Moreover, we repeat the same exercise and change the indicator for technological change and the contribution of ICT capital by considering the ratio ICT/Y. Tables I.19 and I.20 respectively provides estimation results for the long-run equation for the USA and Germany. Column (1) and (3) consider the regression without restriction, while column (2) and (4) constrain the coefficient of the logarithm of output to be equal to 1.

Table I.19: Long-run regression, US economy

	USA, Dependent Variable: $ln\, N$			
	(1) β/s.e.	(2) β/s.e.	(3) β/s.e.	(4) β/s.e.
ln w	-0.98**	-1.05***	-0.92***	-0.99***
	(0.20)	(0.02)	(0.19)	(0.02)
ln Y	0.73***	1.00	0.76***	1.00
	(0.08)		(0.07)	
t^2	0.34	0.14***		
	(0.20)	(0.01)		
ICT/Y			1.09	0.88***
			(1.31)	(0.12)
Constant	2.45	-0.56***	2.02*	-0.73***
	(1.14)	(0.07)	(0.93)	(0.07)
N. obs	875	875	850	850
R^2	0.87		0.83	
N. ind	25	25	25	25

***, **, *: statistically significant at 1, 5, and 10 % level, respectively;
robust standard errors in parentheses

Table I.20: Long-run regression, German economy

	Germany, Dependent Variable: *ln N*			
	(1)	(2)	(3)	(4)
	β/s.e.	β/s.e.	β/s.e.	β/s.e.
ln w	-0.99***	-0.92***	-0.84***	-0.93***
	(0.18)	(0.02)	(0.20)	(0.04)
ln Y	0.60***	1.00	0.62***	1.00
	(0.13)		(0.09)	
t^2	0.22	0.04***		
	(0.19)	(0.01)		
ICT/Y			-0.48	2.13***
			(2.56)	(0.22)
Constant	3.60***	-0.78***	3.08*	-0.73***
	(1.34)	(0.07)	(1.12)	(0.13)
N. obs	875	875	350	350
R^2	0.78		0.86	
N. ind	25	25	25	25

***, **, *: statistically significant at 1, 5, and 10 % level, respectively; robust standard errors in parentheses

For the US, we can observe robust results regarding the effect of wage and output on the level of employment in the long-run: ceteris paribus, an increase in wages decreases employment, while contemporaneous positive movements in the business cycle increase the labor demand. Technological progress is found to be labor saving when the time trend and the constraint is considered, while in the other cases technology has a positive effect on employment in the long-run.

It is reassuring that the estimates of the model for Germany are similar to those of the US, not only qualitatively, but to a large extent also quantitatively. An important exception is that in the regression without any constraints the technology variables, while positive in sign, are statistically insignificant.

I.8.4 Second Stage of the Error Correction Model

After estimating the errors ε of the regression represented in Tables I.19 and I.20, Tables I.21 and I.22 contain the results of the error correction model.

Table I.21: Error Correction Model, US economy

	USA, Dependent Variable: $\Delta\, ln\, N$			
	(1) β/s.e.	(2) β/s.e.	(3) β/s.e.	(4) β/s.e.
$\Delta \ln w$	-0.27***	-0.29***	-0.28***	-0.30
	(0.07)	(0.07)	(0.07)	(0.07)
$\Delta \ln Y$	0.40***	0.41***	0.41***	0.42***
	(0.05)	(0.05)	(0.05)	(0.05)
ε_{t-1}	-0.01	-0.06***	-0.02***	0.43**
	(0.01)	(0.01)	(0.01)	(0.14)
Δt^2	-0.32***	-0.30*		
	(0.07)	(0.12)		
$\Delta\, ICT/Y$			0.36*	-0.07***
			(0.14)	(0.01)
Constant	0.02**	0.02***	0.01	0.01
	(0.01)	(0.00)	(0.01)	(0.01)
N. obs	875	875	650	825
R^2	0.30	0.33	0.58	0.34
N. ind	25	25	25	25

***, **, *: statistically significant at 1, 5, and 10 % level, respectively;
robust standard errors in parentheses

Table I.22: Error Correction Model, German economy

	Germany, Dependent Variable: Δ $ln\ N$			
	(1)	(2)	(3)	(4)
	β/s.e.	β/s.e.	β/s.e.	β/s.e.
$\Delta \ln w$	-0.17*	-0.19*	-0.30*	-0.31**
	(0.07)	(0.07)	(0.11)	(0.10)
$\Delta \ln Y$	0.33**	0.36***	0.41***	0.42***
	(0.10)	(0.12)	(0.07)	(0.10)
ε_{t-1}	-0.02	-0.08***	-0.01	-0.14***
	(0.01)	(0.01)	(0.01)	(0.04)
Δt^2	-0.00	-0.00		
	(0.18)	(0.21)		
$\Delta\ ICT/Y$			0.40*	1.90**
			(0.20)	(0.54)
Constant	0.00	0.00	-0.00	-0.01
	(0.00)	(0.00)	(0.01)	(0.00)
N. obs	875	875	300	300
R^2	0.28	0.25	0.38	0.41
N. ind	25	25	25	25

***, **, *: statistically significant at 1, 5, and 10 % level, respectively; robust standard errors in parentheses

Considering the error correction model, we see that for both countries the short-run effects of wages and output have the same sign as the long-term conditions. The effect of ICT differs across countries: we find a negative impact on employment in the US but a positive effect in Germany.

I.9 Country and Industry Analysis

In this section we extend our analysis to consider not only the US and Germany but all European countries as well as a number of important non-European economies for which data are readily available in the EU KLEMS dataset. The latter group of countries includes Australia, Japan, South Korea and the US. We again analyze the effect of output, wage and technology on employment by means of the error correction method described in the previous section. The regression tables can be found in the Appendix at the end of the report. The results are based on the 25 industries represented in bold in Table I.13. In order to perform our analysis using as much observations as possible for all the countries and industries of the EU KLEMS dataset, the technology variable is constructed in three different ways: 1) as the square of time (t^2), common to all industries and countries, 2) as the ratio of ICT investment to output at the industry level and 3) as ICT TFP derived from the dual approach.[57] While the first two measures allow us to capture the general technological change in the economy as well as the specific technological investment in a single industry, respectively, the last one takes into account possible spillovers as generated by ICT producers.

I.9.1 Technology represented by t^2

Appendix tables 1 to 11 display the results of the regression analysis for the EU aggregate as well as separately for all the countries available in the dataset. The goal of this subsection is to analyze the general effect of technology without including a specific representation of ICT investments. Looking at the long-run regressions, we find a very robust and positive effect of output on employment both for the non EU and the EU countries. The coefficient on wages exhibits a negative and significant sign in most of the countries, exceptions being some small economies in the EU15 (Austria, Belgium and Ireland) and in the EU10 (Cyprus and Malta). Moreover, except for the case of Greece, general technological change does not seem to have a significant impact on employment. Some of these results change when the coefficient of the natural logarithm of output is constrained to be equal to 1 in the long-run (Appendix tables 4-6). While wages enter with a negative sign and are strongly statistically significant in all the countries considered, technological progress is now significant in most of the countries and in EU and non-EU countries alike. Statistically significant positive long-run estimates are calculated for South Korea, the US (non-EU Countries), for Belgium, Denmark, Germany, Greece (EU15), and for Malta (EU10). In contrast, technology seems to be labor saving in Australia, Austria, France, Ireland, Italy, the Netherlands, Portugal, Sweden, the UK, Cyprus and in almost all the Eastern European countries. In our analysis, only Japan, Spain and the Czech Republic do not experience a significant effect of technology.

[57] Details on these indicators and their respective merits and drawbacks can be found in Section I.5.

Looking at the error correction model in the second part of the tables, we can observe that, similar to the long-run regressions, output and wage enter, respectively, with a positive and a negative sign both in the unrestricted and the restricted model. In contrast, technology has only an impact in non EU countries, in some of the EU15 countries and in Hungary. Scrutinizing the countries in which technology has a statistically significant impact on employment, we find that in the short-run a positive effect is only observed for Spain, Ireland and Hungary while the relevant coefficient exhibits a negative sign in Japan, the US, and Austria.

The last two columns of Appendix Table 1 and Table 4 contain the regressions for the aggregated EU15 and EURO area countries. The EU15 represents the EU15 member states for which growth accounting could be performed, namely Austria, Belgium, Denmark, Spain, Finland, Germany, Italy, the Netherlands and the UK, while the countries of the Eurozone are Austria, Belgium, Spain, Finland, France, Germany, Italy and the Netherlands. In the unrestricted model the technology variable enters with a positive sign in the long-run regression and with a negative sign in the ECM model. Both coefficients, however, are statistically insignificant. When constraining the output coefficient to equal one, the technology variable turns statistically significant.

Summarizing the results obtained in the first six tables, we can provide some first economic conclusions and some quantitative analysis of the coefficients. First of all, we prefer to analyze the specification in which employment and output are imposed to grow at the same rate in the long-run (i.e. $\boldsymbol{\beta_2 = 1}$ in equation I.21). Also in these cases, the estimated coefficient of the wage does not seem to change with respect to the previous specifications. For example, looking at the specifications reported in Appendix Table 4 for the most important world economies, if wages were to increase on impact by 1 percentage point, employment will decrease 0.41 percentage points for the EU (0.24 percentage points for the US). On the other hand, the error correction model implies that employment and wages also have an equilibrium relationship, where this increase in wage disturbs the equilibrium, causing employment to decrease another 1.08 percentage points for the EU (with a decrease of 1.05 percentage points for the US). However, the new ``re-equilibration'' is not immediate, occurring over future time periods at a rate given by the coefficient related to $\boldsymbol{\varepsilon_{t-1}}$.

Exploiting a similar analysis, it is also possible to detect the effect of technology when it is represented by the approximation $\mathbf{t^2}$. Employing the error correction model, we see that if the trend increases by one unit , employment will decrease by 0.06 percentage points in the EU15 (0.30 percentage points in the US). However, while we obtain different rates of adjustment for the US and the EU (faster for the US, slower for the EU15), the regressions also suggest that there exists a stronger long-run relationship for the US (0.14 percentage points) than for the EU15 (0.02 percentage points). Looking at the regressions for each country represented in Appendix Table 5, we can observe that there is a positive long-run relationship only for Belgium, Denmark, Germany, and Greece, while for the other countries it seems that technology has a negative long-run impact.

Appendix Tables 7-9 consider the same type of regression but now controlling for product market regulation using the OECD Indicators of Regulation Impact (RC) described in Section I.6.2 and an indicator of Employment Protection Legislation (epl) constructed using the OECD EPL indicator and updated using information contained in the Fondazione Rodolfo Debenedetti Social Reform Database described in Section I.6.3. For this type of regression it is not possible to impose the constraint that output has to be equal to one because of the smaller sample size. In column (1) we add RC to the baseline regression, column (2) includes epl and column (3) reports the regression results when both variables are considered at the same time. Controlling for product and labor market regulations, which are themselves largely insignificant, technology has only a significant (and negative) long-run effect in Italy and Sweden. Finally, Appendix Tables 10-12 reconsider the previous regressions adding an interaction term ($\boldsymbol{t^2} * \mathrm{RC}$) by multyplying the technological term and the OECD Indicator of Regulation. The inclusion of controls for product and labor market regulations in the regressions does not improve the explanatory power and these variables are, in most cases, insignificant. However, one has to bear in mind that by adding indicators for product and labor market regulations the sample size declines markedly and hence the results are not directly comparable to the previous estimates.

Summarizing the results obtained in the first eleven tables of the Appendix, we can observe that while output and wage enter in the regression in a significant and robust way, the general effect of technology is not significant and the impact of the sign is very close to zero. A graphical representation of the behavior of the coefficients in our regression can help to better understand the different impact of these factors on employment. Figures I.6, I.7 and I.8 respectively shows the distribution of the estimated coefficients of the long-run estimates by country when the regressions are performed controlling both for labor and product market regulation, i.e. the results which can be found in column (3) of the Appendix Tables 7-9[58]. In this figure we can clearly observe that while the coefficients of wages and output are centered around negative and positive values respectively, the distribution of technology is centered around zero, suggesting that technology affects employment ambiguously at the national level.

[58] In the Appendix, we present graphs of the distributions of the coefficients when the regression is not controlled for the regulation and most of the other specifications.

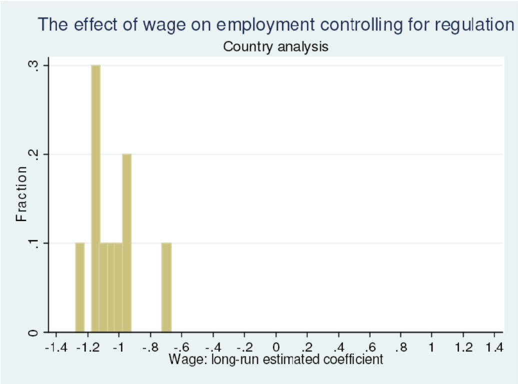

Figure I.6: The effect of wage on employment (country analysis)

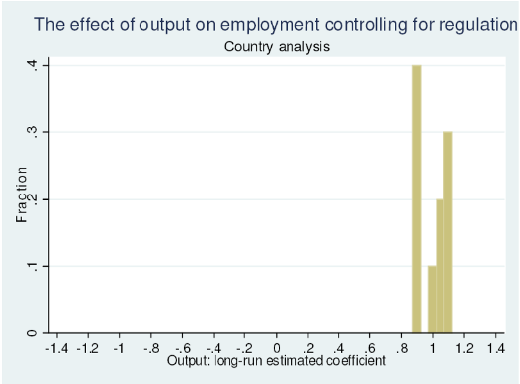

Figure I.7: The effect of output on employment (country analysis)

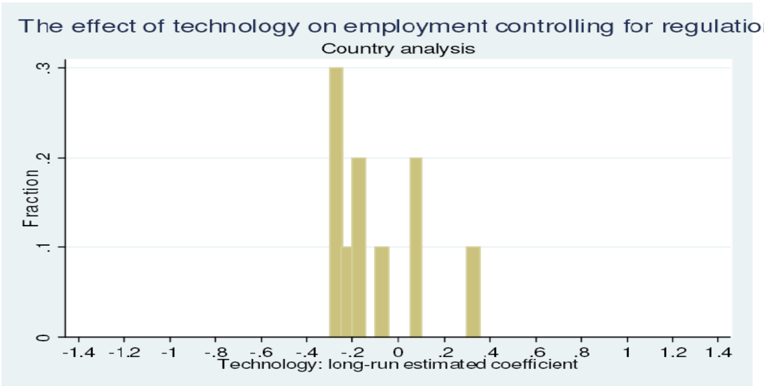

Figure I.8: The effect of technology ($\mathbf{t^2}$) on employment (country analysis).

Appendix Tables 12-21 report the results of the same type of analysis but now by industry: when the basic specification is considered, the effect of wage and output are the usual ones, while we observe a labor saving effect of technology for other non-metal, machinery, electrical, transport, post, construction in the long-run and for pulp, manufacturing, post, electricity and financial in the short-run. Similar to the country regressions, technology is rendered statistically insignificant once product and labor market regulations are controlled for. Similar to the graphs related to the country level analysis, Figures I.9-I.11 provide the distribution of the long-run estimates for the industry analysis. Also notice the similar distribution for output and wage. Even if the regression coefficient is more often negative than positive, also the distribution of technology is similar to the one obtained by the country analysis.

Figure I.9: The effect of wage on employment (industry analysis)

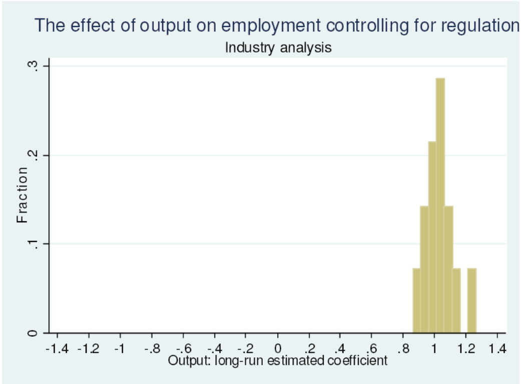

Figure I.10: The effect of output on employment (industry analysis)

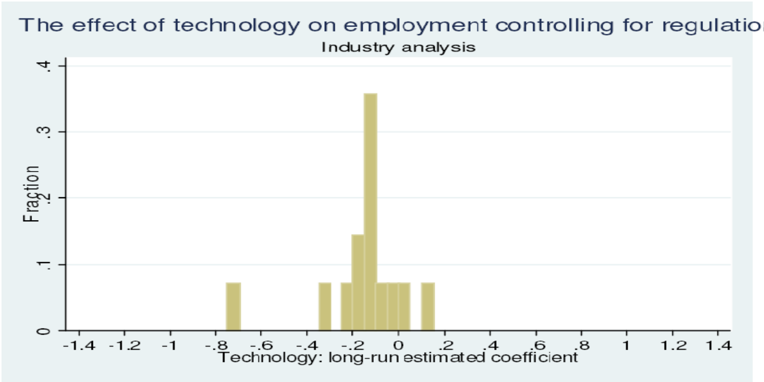

Figure I.11: The effect of technology ($\mathbf{t^2}$) (industry analysis)

I.9.2 Technology represented by I_{ICT}/Y

We now represent technology by the ratio of investment in ICT to output. The goal of this subsection is to analyze the general effect of technology including a specific representation for ICT investments. The results of the basic specification are shown in Appendix Tables 22-27. With respect to wages and output the results are similar to those found in the previous section. However, the results suggest that neither in the long-run nor in the short-run technology has any impact on employment. However, when we restrict the coefficient of output to be equal to 1, we find statistically significant effects of ICT. In the long-run, technology has reduced employment in Australia, Austria, Finland, Italy, the Netherlands and in the UK, while it has boosted employment in Japan, South Korea, Denmark, Germany and Sweden. Regarding the short-run, technology has a statistically significant and positive effect only in Australia and South Korea, Austria and Germany. However, similar to the analysis we have run in the previous subsection, once we control for product and labor market regulations, technology loses its significance, except in Germany and Sweden, where we can observe a positive effect in the short-run.

Concentrating our attention on Appendix Tables 25-27, where we restricted the coefficient of the output to be equal to one, the short-run impact changes sign from negative to positive. Comparing Germany and the US, we can observe that if technology were to increase one point, employment will immediately increase 1.90 and 0.43 percentage points respectively for Germany and the US. But, the error correction model implies that employment and wage also have an equilibrium relationship, where this increase in wages disturbs the equilibrium, causing employment to increase another 0.30 percentage points for Germany and 0.06 percentage points for the US until the long-run increase of 2.13 percentage points (for Germany) and 0.88 percentage points (for US) is not reached. Appendix Tables 28-48 display the regressions results for separate industries: again, technological change is rendered statistically insignificant once epl and RC are considered (the exceptions being the transport and the financial sector).

Similar to the previous section, the results obtained in Tables 26-48 of the Appendix confirm that output and wage enter in the regression in a significant and robust way, while a direct measure of ICT is not significant and the impact of its sign is very close to 0. Figures I.12, I.13 and I.14 respectively show the distribution of the coefficient of the long-run estimates by country when the regressions are performed controlling both for labor and product market regulation. In these figures we can clearly observe that while the coefficients related to wages and output are centered around negative and positive values respectively, the distribution of technology is centered around 0 suggesting that technology affects employment ambiguously at the national level.

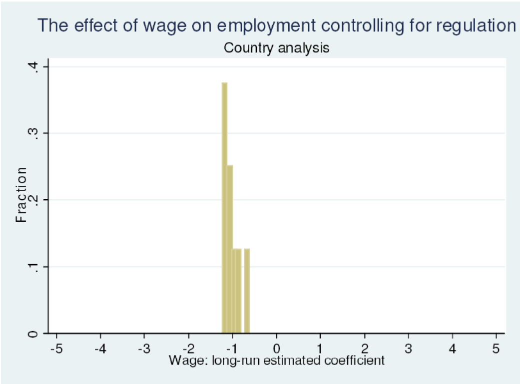

Figure I.12: The effect of wage on employment (country analysis)

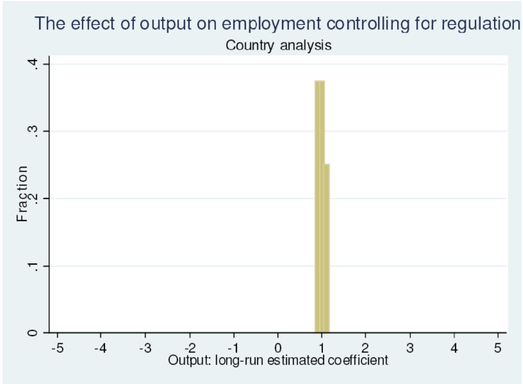

Figure I.13: The effect of output on employment (country analysis)

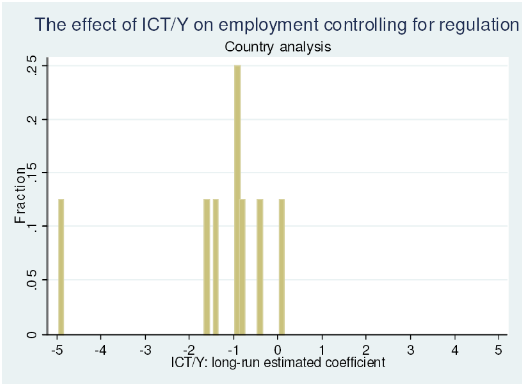

Figure I.14: The effect of technology (ICT/Y) on employment. (country analysis)

Concentrating our attention on the industry level analysis, we obtain Figures I.15-I.17, confirming a robust effect for wage and output and an ambiguous one for ICT.

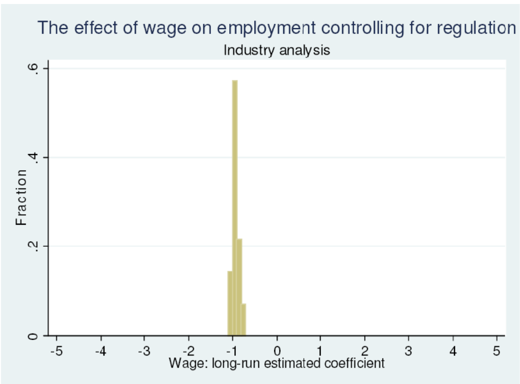

Figure I.15: The effect of wage on employment (industry analysis)

Figure I.16: The effect of output on employment (industry analysis)

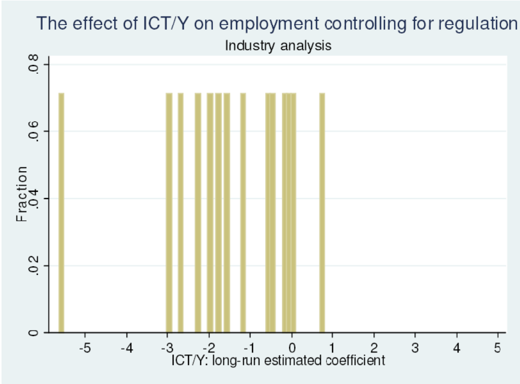

Figure I.17: The effect of technology (ICT/Y) on employment (industry analysis)

I.9.3 Technology represented by (ICT TFP)

Finally, Tables 45-48 report the regression results for the case in which we account for general spillovers by ICT producer. In order to have a measure available for most of the countries, we constructed the measure as the decrease in the price of ICT goods multiplied by the share of the ICT industries in the total economy. This analysis can be performed at the country level, imposing long-run restriction on output is, however, not feasible. Again, the usual robust effect of wages and output on employment can be observed. However, while in the long-run ICT TFP does not have any impact, the error correction model suggests that technological spillovers have had a significant and negative effect in Japan, South Korea and in Austria, Denmark, Finland, and in the United Kingdom. This result is not robust, however, to the inclusion of controls for labor and product market regulations.

I.10 Conclusions

The results of the previous two sections lead us to several conclusions with ramifications for policy. Important lessons can also be learned about the appropriate level of aggregation for econometric analysis, the variables considered, and the econometric techniques adopted. Regarding the level of aggregation, we have seen that some specifications related to the aggregate level for EU15 and EURO area lead to different results from those originated from individual, country-level analyses. Moreover, the error correction model and the long-run specification are useful for disentangling long- and short-run effects. Finally, different types of proxies for technology, the square of time, the ratio of ICT investment to output, and the contribution to TFP given by the ICT producers, give disparate and sometimes inconsistent results.

Overall, the effect of technology on aggregate, sectoral labor demand was considerably less robustly estimated than the standard covariates (wages and output), which entered almost always significantly and with expected signs. Especially when product and labor market regulations were accounted for, ICT variables tended to be statistically insignificant. This is especially true in the long-run. We considered three different measures of ICT-technology: 1) a "vanilla" time trend, 2) more direct measurements of ICT investment, 3) measures of ICT spillovers. For these reasons, in order to study the direct impact of ICT on employment, we choose among the different models tested the error correction model and the long-run specification containing as proxy of technology change the ratio of ICT investment to output for three main reasons: 1) it is a more flexible measure compared to time squared, 2) it contains a direct measure of ICT, 3) it allows to run the analysis for several countries and\or industries, also imposing restrictions at the long-run equation.

The main results of our empirical analysis are the following: while wage and output provide robust results and respectively enter with a negative and a positive sign in our labor demand regressions, the measures we used to represent technology give conflicting and ambiguous results. When a general measure of technology is considered, technological change has usually a negative short-run and a positive long-run effect on employment in the most important industrial countries and the aggregate for the EU15 considered. On the other hand, the sign of the long-run effect changes when the regressions are performed at a country level and the significance tends to disappear when labor and product market regulations are controlled for. Moreover, when a direct measure of ICT (i.e. the ratio of ICT investment to output) is included in the specification, we observe that new technologies can present different signs both in the short and in the long-run effect. Nevertheless, once a measure of total factor productivity contributed by ICT goods is considered, technology seems to have a general negative impact on employment. Those results suggest that even if in Europe technology or spillover effects can have a labor saving effect, ICT investment can be a positive source not only in increasing productivity, but also in stimulating employment. The caveat should be added, however, that the inclusion of indicators for product and labor market regulations reduces the sample size markedly and hence the results are not directly comparable to the previous estimates. Nevertheless, when the role of institutions is considered in our specifications, the role of technology is no longer significant.

These findings are consistent with an economic model in which short-run fluctuations to total factor productivity and technical progress represented by ICT affect employment either positively or negatively in the short-run, but these effects are generally vitiated or completely offset in the long-run. This result would be consistent with a “small economy” model in which capital is perfectly mobile across labor markets while labor is relatively inelastically supplied in the long-run, but possible elastically supplied in the short-run. Under such conditions, shocks to labor demand induced by technological change will lead to short-term fluctuations in employment, but over time these shifts ultimately impact only the absolute and relative remuneration of labor in the respective sectors. Naturally, to the extent that international or intersectoral migration is possible, the inelastic labor supply assumption may be questioned.

Part II: Offshoring

II.1 Introduction

The rapid advances in information technology and the sharp decline in communication costs have significant impact on the nature of international trade. For centuries, countries mostly exchanged final goods and raw materials. In contrast, the recent wave of globalization is characterized by the diffusion of production stages across national boundaries. In this context, ICT allows for the coordination of tasks performed at different locations, facilitates the transmission of instructions and permits the electronic transmission of output. These developments enable firms to take advantage of international cost differences and allow for a finer international division of labor. Moreover, many service tasks that were once considered as non-traded are almost freely tradable today, as communication costs have dropped to almost zero. A frequently discussed example is the steady migration of US call centers to India.

The public debate in developed countries on the effects of offshoring has focused on its labor market effects. In particular, there is widespread concern about the impact on employment. Part II of this study will therefore provide an in-depth analysis of the issue. As the broader context of the report is the interaction between ICT and employment, this chapter puts special emphasis on ICT-induced offshoring. Undoubtedly, ICT is particularly important for the rapid expansion of *service* offshoring as it increases the tradability of services and allows for the globalization of market services. Rapid developments in ICT provide increasing opportunities for offshoring. In particular, "knowledge work", such as data entry and information processing (IT services), and research and consultancy services (ICT-enabled business services) can be carried out remotely via the Internet and tele- and video-conferencing (cf. OECD, 2004[59]). Nevertheless, ICT may also have contributed to the boom of material offshoring, for instance by facilitating the communication between different production units. Hence, we will be concerned with both types of offshoring and do not focus exclusively on service offshoring.

Part II is organized as follows. First, offshoring is defined. This step is all the more important since at present no commonly accepted definition exists. Second, the employment effects of offshoring are discussed from a theoretical perspective. In particular, it is shown that offshoring may have both positive and negative employment effects. Thus, (the sign of) the net employment effect cannot be unambiguously determined by theory. We then go on and discuss different approaches to measure offshoring. Finally, we turn to the empirical evidence on the employment effects of offshoring and provide an econometric framework that can readily be used to assess empirically the employment effects of offshoring in a European context. We perform the empirical analysis with Germany as an example.

[59] OECD (2004), "OECD Information Technology Outlook 2004", OECD.

II.2 Defining Offshoring

Any analysis of the employment effects of offshoring has to start with a proper definition of the phenomenon. This is because no commonly accepted definition of offshoring exists. In particular, the terms "offshoring" and "outsourcing" are often used interchangeably in the public debate but also in the scientific community.

In order to define offshoring and its two forms of manifestation, it is useful to break up the production options of a company along two dimensions. First, an enterprise can either produce in-house or outsource the production of goods and services to an unaffiliated supplier. Second, the production may take place in the home country or offshore, i.e. in a foreign country. By combining the two dimensions, four different production options' can be distinguished between (see Table II.1).

Table II.1: Offshoring vs. outsourcing: production options of a company

Location of production	Internalized production (in-house)	Externalized production (outsourcing)
Home country	Domestic in-house production	Domestic outsourcing
Foreign country (offshoring)	Offshore in-house sourcing	Offshore outsourcing

Source: UNCTAD (2004)[60], US Government Accountability Office (2004)[61]

First, a company can engage in domestic in-house production, i.e. production takes place within the company and within the home country. Second, the company may outsource partially or completely the production of goods and service to a non-affiliated domestic supplier (domestic outsourcing). Third, the production of goods and services can be transferred to a foreign affiliate of the firm, i.e. production remains within the firm but takes place in a foreign country (offshore in-house sourcing). Fourth, offshore outsourcing designates the contracting-out of production activities to a foreign non-affiliated supplier. The third and fourth production options are classified as offshoring. The defining characteristic of offshoring is therefore the cross-border aspect and not the externalization of production.

Another criterion that is sometimes used to define offshoring is the displacement of domestic production and employment (cf. OECD, 2007[62]; US Government Accountability Office, 2004). Importing intermediate inputs from a foreign affiliate will then only be classified as offshore

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[60] UNCTAD and Roland Berger Strategy Consultants (2004), "Services Offshoring Takes Off in Europe – In Search of Improved Competitiveness", Summary Report, UNCTAD, Geneva.
[61] US Government Accountability Office (2004), "International Trade: Current Government Data Provide Limited Insight into Offshoring of Services", US General Accounting Office (GAO-04-932), www.gao.gov/cgi-bin/getrpt?GAO-04-932.
[62] OECD (2007), "Offshoring and Employment: Trends and Impacts", OECD.

outsourcing, if these inputs were previously produced in domestic operations. We will largely follow the notion that offshoring involves the *relocation* of a production activity abroad. However, readers should note that – according to Table II.1 – in a broader sense offshoring is not necessarily associated with a displacement of domestic production (and jobs). Before proceeding it is helpful to briefly take a closer look at the two types of offshoring.

Offshore in-house sourcing

If one concentrates on offshoring that involves the relocation of an activity abroad, then offshore in-house sourcing designates cases in which a company moves an *existing* production activity to a foreign affiliate. The latter may already exist or may be newly established (so-called "greenfield" affiliates). As an example, you may consider a German car producer that moves its accounting department from its domestic operations to an affiliate based in India. Hence, offshore in-house sourcing concerns multinational enterprises (MNEs) and involves foreign direct investment (FDI).

In general, offshore in-house sourcing is then characterized by the following three characteristics (OECD, 2007):

1. Total or partial cessation of a production activity in the home country.
2. Production of goods and services that were previously domestically produced is now undertaken by new or existing foreign affiliate.
3. The part of the production that was previously consumed domestically is now imported from the foreign affiliate.

Offshore Outsourcing

In contrast to offshore in-house sourcing, offshore outsourcing does not involve foreign direct investment and is therefore not restricted to multinational enterprises. Offshore outsourcing refers to cases in which a company contracts out an existing production activity to a non-affiliated firm that is located abroad.[63] To return to the previous example: if the German car manufacturer were to close its in-house accounting department and instead purchases the corresponding service from a foreign-based (non-affiliated) company, it would engage in offshore outsourcing.

Offshore outsourcing generally shares the following three characteristics (OECD, 2007):

1. Total or partial cessation of a production activity in the home country.

[63] In principle, a company could also outsource an activity to a *domestic* firm, which in turn subcontracts abroad.

2. Production of goods and services that were previously produced domestically are contracted out to a non-affiliated foreign-based firm.
3. The part of the production that was previously consumed domestically is now imported from the foreign subcontractor.

II.3 The Employment Effects of Offshoring: A Theoretical Perspective

The negative short-term effects of offshoring on employment have received a lot of public attention. The short-term employment effects are relatively easy to observe and can often be directly linked to offshoring. If a car manufacturer relocates its accounting department abroad, workers that were previously employed in the (in-house) accounting department will lose their job as a direct consequence of the decision.

However, offshoring may also affect employment indirectly, e.g. through its alleged impact on firm productivity. Such indirect effects are far more difficult to observe and are often perceived to be unrelated to offshoring. For instance, firm productivity is not only driven by offshoring but by a bulk of other factors such as ICT or managerial organization. Therefore, it is very difficult to isolate the effect of offshoring on productivity. And even if this were possible, quantifying the subsequent effects on employment also presents a serious challenge. Given these difficulties, the public focus on the short term, direct effects of offshoring is understandable but might miss important indirect and possibly positive effects on employment.

The aim of the present section is therefore to give a short but comprehensive overview of the different channels through which offshoring can theoretically influence employment. The section starts with a description of the short-run employment effects, and will then turn to the indirect employment effects that are likely to take effect only with some time delay.

II.3.1 Job Displacements in the Short-Run

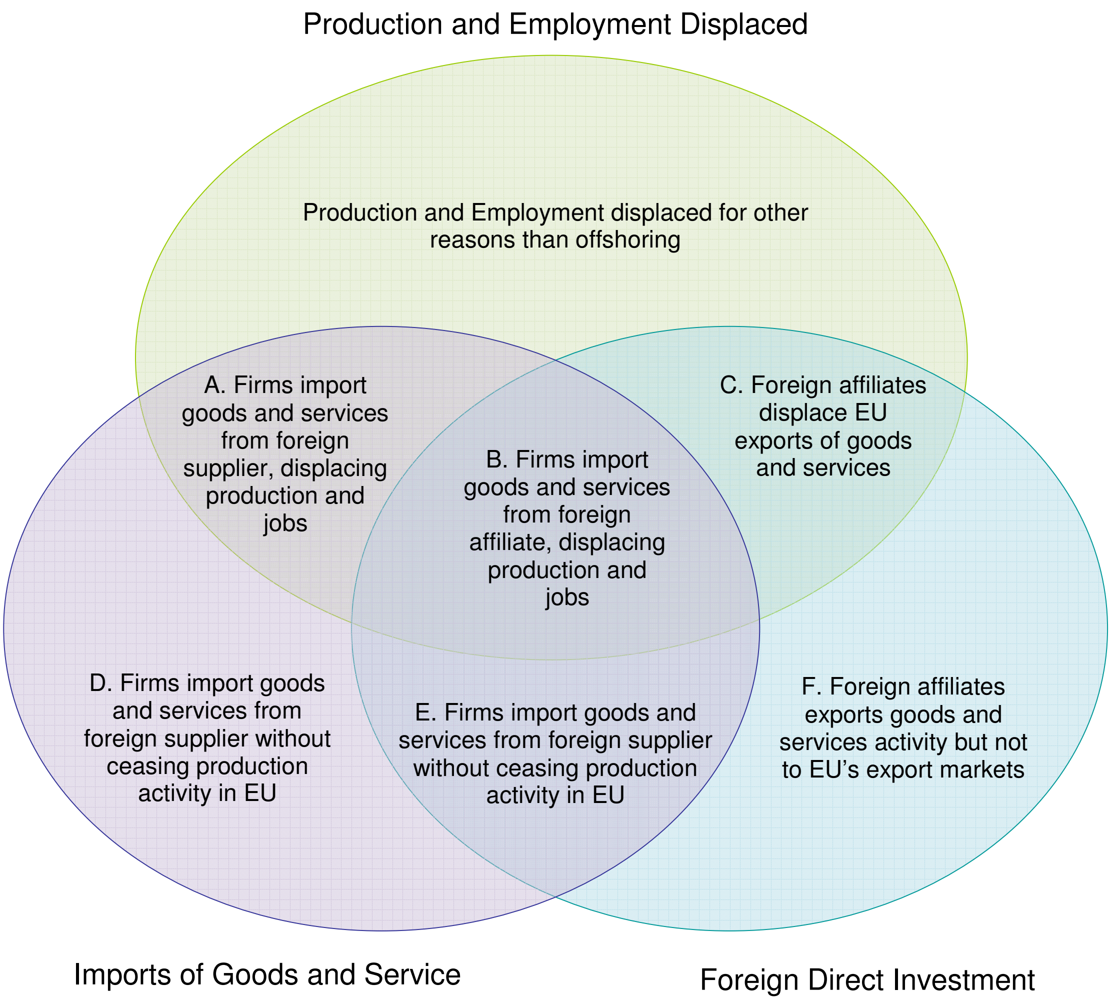
In Section II.2, offshoring has been defined as a relocation of domestic production to either a foreign affiliate or to a foreign (non-affiliated) supplier. The part of relocated production that was previously consumed domestically is then re-imported. Hence, by definition, offshoring involves the cut back of domestic production and jobs. Figure II.1 provides an overview of the interaction between imports of goods and services, foreign direct investment and displaced production in, say, the European Union (EU).

Situations A, B, and C are directly related to offshoring as defined in the previous section. A refers to offshore outsourcing. Contracting out an existing production activity implies the displacement of production in the EU; the corresponding jobs are then lost as a direct consequence of offshore outsourcing. Situations B and C describe the short-term production and employment effects from offshore in-house sourcing. The production transferred to a foreign affiliate may have been intended for exports or for domestic consumption. While in the latter case production is re-imported to the EU, in the former one production is directly exported to the destination market and no intra-firm imports are observed. In either case, offshoring implies the short-term loss of employment associated with the transferred production activity. Note, however, that situation C is potentially difficult to observe in official statistics since production does not return to the EU.

In principle, these negative employment effects can be reinforced if other domestic subcontractors are also affected by the decision to offshore. For instance, the production unit transferred may itself have contracted out the production of intermediate inputs to a European supplier and the latter may lose the (sub-) contract in the wake of the offshoring decision. The European supplier may also feel obliged to follow the production unit abroad. European employment will then shrink even further in the short-run.

A broader definition of offshoring would also include the less obvious scenarios D, E, and F. These activities have in common that they do not involve a relocation of production activities. For instance, E describes a situation in which domestically consumed production of goods and/or services is imported from a foreign affiliate. However, the production activity was never located in the EU in the first place and hence domestic employment is not directly affected by the decision to invest abroad. Of course, one may argue that in the absence of the investment the production unit would have been created in the EU and, thus, (future) employment is nevertheless displaced. However, for this line of reasoning one would have to infer the company's behavior in case the activity would not have been created abroad. Clearly, this is a difficult exercise, and it would be mistaken to conclude that any production activity that may have arisen abroad could potentially also be carried out domestically. Hence, while the reader should bear in mind that also situations D, E, and F may be accompanied with job displacement, the focus of the analysis will be on A, B, and C.

Figure II.1: Offshoring and short-term employment effects



Source: US Government Accountability Office (2004)

II.3.2 Offshoring as Technological Progress: The Productivity Effect

A number of theoretical contributions have highlighted the analogy between fragmentation of the production process and technological change. In particular, an important literature strand has modeled fragmentation as a technological improvement that allows firms to break down the production process into two (or more) discrete component parts. Generally speaking, the possibility to import component parts that previously had to be produced at home can increase the final good output for any given quantity of inputs. But this constitutes a definition of technological progress. The corresponding labor market effects of offshoring in this class of models are not easily summarized and depend crucially on the industry in which fragmentation occurs and the factor intensities of the component parts.

Nevertheless, important insights can be gained from this literature. In contrast to public perception, offshoring may well increase labor demand by boosting productivity. For instance, Jones and Kierzkowski (2001)[64] analyze the effects of fragmentation occurring in a single industry. In their framework, fragmentation is analogous to industry-specific technological progress and the factor that is used intensively in the industry will benefit from these productivity gains. Hence, according to their analysis, in labor-intensive industries workers may well profit from the productivity-enhancing effect of fragmentation.

In a recent paper, Grossmann and Rossi-Hansberg (2006)[65] developed a new modeling framework. In their setup the production of a good involves a continuum of tasks performed either by low-skilled ("L-tasks") or high-skilled workers ("H-tasks"). In the simplest version of the paper, offshoring is restricted to L-tasks and firms can accordingly choose to perform these tasks at home or abroad. Offshoring allows firms to exploit lower wages abroad but makes it more difficult to monitor and coordinate workers. These costs are reflected in additional input requirements. The authors further assume that some tasks are more easily offshorable than others and postulate the existence of two industries, which differ in terms of their skill intensities. The study then analyses the labor market effects of an improvement in communication and transportation technologies modeled as a reduction in the costs associated with moving an L-task offshore.

One of the main achievements of the paper is the identification of a productivity effect[66] that works in favor of the low-skilled or, to put it in more general terms, in favor of the factor whose tasks are now more easily performed abroad. The authors show that an improvement in communication and transportation technologies will generate cost savings similar to an economy-wide increase in the productivity of the low-skilled and will therefore boost labor

[64] Jones, R. and Kierzkowski, H. (2001), "Globalization and Consequences of International Fragmentation", in R. Dornbusch, G. Galvo and M. Obsfeld, eds., *"Money, Factor Mobility and Trade: Festschrift in Honor of Robert A. Mundell"*, MIT Press, Cambridge, Massachusetts.
[65] Grossmann, G.M. and Rossi-Hansberg, E. "Trading Tasks: A Simple Theory of Offshoring", *NBER Working Paper No. 12721*, 2006 (forthcoming in the *American Economic Review*).
[66] The (negative) terms-of trade and job loss effects also identified are discussed in Sections 3.1 and 3.3.

demand. Cost savings are generated for two reasons. First, tasks that have been previously performed at home are now relocated abroad where they can be performed at lower costs. Second, tasks that have already been offshored are now even cheaper performed abroad since e.g. the costs of monitoring them have fallen even further.[67]

Both the high- and the low-skill intensive industry benefit from these costs savings. However, the industry intensive in low-skilled labor will benefit more because their share of L-tasks in total costs is larger. Hence, the low-skill intensive industry expands relative to the high-skill intensive industry. Consequently, the productivity effect of offshoring will increase labor demand for the unskilled. Grossmann and Rossi-Hansberg (2008) only consider perfect factor markets and analyze the effect on factor prices. The identified productivity effect then increases the wage rate of unskilled workers while leaving that of skilled workers unchanged.[68]

Mitra and Ranjan (2007)[69] depart from perfect factor markets and study a model in which unemployment arises owing to search frictions in the labor market. Clearly, such a model framework is of particular interest in the context of the present study, which is concerned with the employment rather than the wage effects of offshoring. The authors find that the productivity enhancing (cost reducing) effect of offshoring can reduce the unemployment rate and increase wages, a finding that resembles the results derived by Grossmann and Rossi-Hansberg (2008) in a model with perfect factor markets.

An aspect related to the productivity enhancing effect is the impact of offshoring on the (price) competitiveness of enterprises. With falling costs for imported intermediate inputs, enterprises may either keep their prices constant thereby increasing their margins or they will pass on the reduced input prices to consumers and gain market shares (OECD, 2007). Depending on the market environment this may induce firms to invest and produce more and hence to create new jobs.

II.3.3 Terms of Trade and Relative Price Effects

A further indirect channel through which offshoring may (adversely) affect labor demand are the terms of trade of a country. The terms of trade refer to the relative price of a country's exports to its imports. Standard trade theory suggests that a nation will benefit from the improvement of its terms of trade, basically because it has to pay less for the products it imports, that is, it has to give up fewer exports for the imports it receives. How can the rise in offshoring affect a country’s

[67] According to the envelope theorem, the first effect is negligible for small changes in the offshoring costs.
[68] The authors also extend the model to allow for offshoring of skill-intensive tasks and come up with similar findings.
[69] Devashish, M. and Ranjan, P. (2007), “Offshoring and Unemployment”, *IZA Discussion Paper* 2805.

terms of trade? As Samuelson (2004)[70] pointed out, the terms of trade will indeed deteriorate if offshoring boosts foreign productivity in sectors in which the country under consideration is a net exporter.

To see the possibility, consider a concrete example taken from Leamer (2007)[71] that illustrates an argument originally put forward by Deardorff (2001)[72]. Leamer (2007) sets up a Ricardian type of model with just two goods, apparel and software, and two countries, the US and India. While workers in both countries are equally productive in making apparel, American programmers are more productive in writing software. This is illustrated in the upper panel of Figure II.2 that depicts the production possibility frontiers of typical US and Indian workers. In Leaner's example the American technological superiority in software stems from geography and history. And since writing software requires face-to-face contact, Indian workers are initially too far away from the US as to benefit from agglomeration externalities.

The corresponding equilibrium is illustrated in the middle panel of Figure II.2. India and the US specialize in apparel and software, respectively, as shown by the solid circles. Production can be traded at prices prevailing in the world market. The resulting consumption options for an individual worker in either of the two countries are represented by the two dotted lines, where the slopes are given by relative prices. Consumption choices are determined by consumer preferences that are in Figure II.2 represented by indifference curves. US workers will initially gain from trade and their productivity advantage in software will allow them to sustain higher real wages and living standards compared to their Indian counterparts.

Now suppose that improvements in communication technologies allow firms to fragment the programming of software. Indian workers can now participate via video conferences and internet telephony at zero costs in the conversations of their American colleagues. Hence, American firms will start using (cheap) Indian labor for writing software. Consequently, the supply of software to world markets increases and accordingly prices fall. The US experiences a deterioration of its terms of trade while India's terms of trade are rising. The process will only stop when real wages and living standards in the two countries are alike. In the final equilibrium, production technologies in the two countries have converged and US workers will no longer benefit from free trade (see lower panel of Figure II.2).

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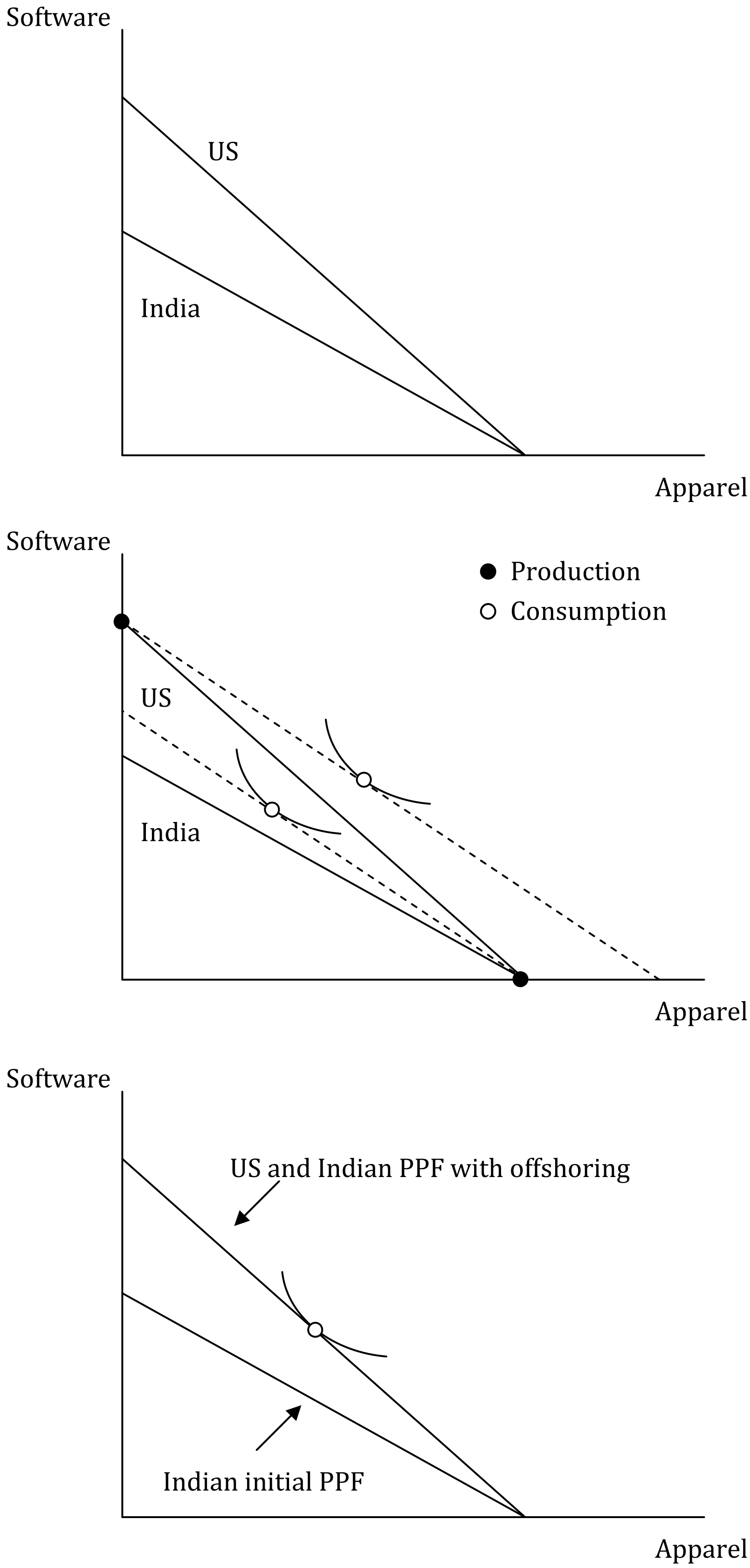
[70] Samuelson, P.A. (2004), "Where Ricardo and Mill Rebut and Confirm Arguments of Mainstream Economists Supporting Globalization", *Journal of Economic Perspectives,* 18, 135-46.

[71] Leamer, E.E. (2007),"A Flat World, a Level Playing Field, a Small World After All, or None of the Above? A Review of Thomas L Friedman's *The World is Flat*," Journal of Economic Literature, 45(1), 83-126.

[72] Deardorff, A.V. (2001), "Fragmentation in simple trade models," *The North American Journal of Economics and Finance*, 12(2), 121-137.

Figure II.2: Terms of trade effect of offshoring



While Grossmann and Rossi-Hansberg (2008) use a different modeling strategy, they also identify a terms of trade effect that works against the production factor whose tasks are more easily offshored after an improvement in communication and transportation technologies. In their model, improvements that are associated with lower costs of moving an L-task offshore will generate cost savings. These cost savings will benefit both labor-intensive and skill-intensive producer, but, as already argued in Section 3.2, the former will profit more. Accordingly, relative world output of the labor-intensive good will increase and consequently the relative price of the good will fall. These relative price movements are then mirrored in falling relative factor prices for low-skilled workers. Consequently, offshoring is found to generate relative price movements that harm the production factor whose work is now more easily produced abroad.

II.3.4 Offshoring in Unionized Labor Markets

An important feature of many labor markets in (continental) Europe is the prevalence of collective bargaining regimes and relatively strong trade unions. Especially in the European context offshoring might also influence employment (and wages) by affecting the wage bargaining between employers and employees. A commonly expressed concern in that respect is that globalization in general and offshoring in particular will erode the bargaining power of workers forcing them to accept lower wages or longer working hours (OECD, 2007). But if trade unions set wages above the market clearing wage rate, such wage cuts can boost employment.

To shed light on the issue at hand, a number of theoretical papers have analyzed the (wage and employment) effects of offshoring in unionized labor markets. Unfortunately, the results are far from conclusive. Depending on the specific assumptions, the models often yield contradictory predictions about the wage and employment effects of offshoring. In order to understand under which circumstances positive or negative employment effects can be expected, it is helpful to briefly consider in turn the most important modeling assumptions.

First, Skaksen and Sørensen (2001)[73] highlight that the labor market effects of foreign direct investment (offshore in-house sourcing) will depend on the degree of complementarity between host and home country activities. If activities are highly complementary, foreign direct investment will imply relatively small employment losses or might even cause domestic employment to expand. Skaksen and Sørensen (2001) also show that - contrary to public perception – union wages might actually increase in multinational firms. Intuitively, the share of domestic wages in the total wage bill of an enterprise is relatively small in multinational firms. Provided that host and home country activities are sufficiently complementary unions can then put through higher rather than lower wages.

[73] Skaksen, M.Y. and Sørensen, J.R. (2001), "Should trade unions appreciate foreign direct investment," *Journal of International Economics*, 55(2), 379-390.

A similar result has been established by Lommerud et al. (2005)[74]. Their study analyzes the incentives of unionized firms to outsource intermediate goods production to foreign non-affiliated subcontractors. The authors also find that international outsourcing (offshore outsourcing) *increases* the bargained wage. From the perspective of the union international outsourcing 'exogenizes' a larger share of wage costs. Hence, the wage elasticity of labor demand declines and unions will enforce higher wages for the remaining in-house production. However, as Braun and Scheffel (2007)[75] show, the stark result of Lommerud et al. (and to some extent also the results presented in Skaksen and Sørensen, 2001) depend on the timing of events. In particular, Lommerud et al. (2005) view outsourcing as a long-term decision that concerns the organizational structure of a firm. Therefore, they assume that the wage bargaining takes place *after* the outsourcing decision has been made. Allowing the degree of outsourcing to adapt to changes in the bargained wage, Braun and Scheffel (2007) show that the ease with which a firm can outsource parts of their production to a foreign supplier has an ambiguous effect on the wage set by the union. Therefore, the timing of events is an important aspect that will influence the labor market effects of offshoring.

Finally, Skaksen (2004)[76] distinguishes between realized and potential (but non-realized) international outsourcing. He shows that unions agree to exercise wage restraint when faced with the mere *threat* of firms to outsource the production of an intermediate good. Since unions demand inefficiently high wages in the model, the reduction in the bargained wage will increase welfare and employment. For the empirical analysis, of course, the result is problematic since the positive employment effect materializes even though outsourcing never actually occurs.

II.3.5 Summary of the Theoretical Considerations

In this section, it has been shown that – from a theoretical point of view – the (sign of the) overall employment effect of offshoring is not straightforward to determine. In the very short-run, it should reduce employment simply via direct replacement of domestic jobs. Offshoring can also depress labor demand by boosting foreign productivity in sectors in which the home country is a net exporter (thereby deteriorating the terms of trade of the home country). However, offshoring should also enhance firm productivity and strengthen competitiveness. This has the potential to *increase* domestic employment, at least in the medium term. Finally, offshoring might also shift the balance of power in collective agreements. However, there is no conclusive evidence on the employment (and wage) effects of offshoring in unionized labor markets.

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[74] Lommerud, K.E., Meland, M., and Sørgard, L. (2003), "Unionised Oligopoly, Trade Liberalisation and Location Choice," *Economic Journal*, 113(490), 782-800.
[75] Braun, S. and Scheffel, J. (2007), "A Note on the Effect of Outsourcing on Union Wages," *SFB 649 Discussion Paper* 2007-034.
[76] Skaksen, J.R. (2004), "International outsourcing when labour markets are unionized," *Canadian Journal of Economics*, 37(1), 78-94.

II.4 Measuring Offshoring

II.4.1 Requirements in Present Context

Measuring offshoring presents a challenge. In the European context, there exists no regular survey in this area and hence no direct estimate of the phenomenon. Therefore, the major challenge ahead is to provide a comprehensive and consistent empirical assessment *despite* the far-reaching data limitations.

In this section, we will discuss various indirect indicators of offshoring and evaluate their appropriateness given the aim of the present study. In a European context it is of particular importance to establish comparable estimates of the extent of offshoring (and its effect on employment) for the different European countries. Therefore, *comparable* data that can be used to actually calculate the respective measure of offshoring should readily be available. Empirical work also has to accommodate the complexity of the offshoring phenomenon by breaking up the employment effect of offshoring along several dimensions. An appropriate indicator should therefore be able to distinguish between, e.g., material and service offshoring or between offshoring to developing and developed countries.

II.4.2 Discussion of Indicators

Value-Added in Production

Brief Description

A first indicator for the outsourcing intensity of an industry j is the share of domestic value-added in production

$$VAP_j = \frac{domestic\ value - added\ in\ sector\ j}{output\ of\ sector\ j}$$

In general, the more production is externalized the lower is the share of domestic value-added in total output. Hence, the indicator is an inverse measure of the outsourcing activities of an industry.

Discussion

In general, the measure is a reasonable outsourcing indicator. However, in the present context it is not appropriate since the indicator does not differentiate between domestic and offshore outsourcing. In particular, a decrease in the indicator might be entirely due to a rise in outsourcing to domestic suppliers. Moreover, but less important, the indicator cannot separately quantify the extent of material and service outsourcing.

Foreign Direct Investment

Brief Description

As described in Section II.2, offshore in-house sourcing typically involves a capital flow to the destination country, either in order to set up a new or to expand an existing affiliate. Hence, a natural measure of offshoring would be FDI flows and/or stocks. While direct investment in general is to a large extent driven by market access motives, the relocation of production abroad is most often induced by cost saving motives (cf. OECD, 2007). Consequently, for offshore in-house sourcing FDI flows from developed to less-developed and to emerging economies should be of particular relevance.

Discussion

While foreign direct investment can serve as an indicator of offshore in-house sourcing, it has the major shortcoming that it does not take into account offshore outsourcing. International sub-contracting does not involve a direct investment flow. Moreover, FDI is not necessarily associated with the relocation of production. This is especially true for horizontal foreign direct investment that is undertaken in order to gain access to foreign markets and serve the local customers. Finally, as noted by the OECD (2007), offshore in-house sourcing may involve purely financial transactions, especially in the case of expanding an already existing affiliate.

Imported Intermediates / Total Inputs

Brief Description

Feenstra and Hanson (1996, 1999)[77] propose the share of imported intermediates in total non-energy inputs as a measure of offshoring. The authors distinguish between a wide and a narrow measure of offshoring. The broadly defined wide indicator of offshoring takes all inputs that a domestic industry imports from abroad into account. In contrast, the narrow definition considers only intermediates imported from the same industry abroad. For instance, intermediate products that the textile sector in Germany imports from some foreign textile sector will count as offshoring in the narrow and in the wide sense. Intermediates imported from

[77] Feenstra, R.C. and Hanson, G.H. (1996), "Globalization, Outsourcing, and Wage Inequality", *American Economic Review*, 86(2), 240-45.
Feenstra, R.C. and Hanson, G.H. (1999), "The Impact of Outsourcing and High-Technology Capital on Wages: Estimates for the United States 1979-1990," *Quarterly Journal of Economics*, 114(3), 907-940.

a foreign food sector by the German textile sector will only be taken into account by the wide offshoring measure.

Formally, for a given industry *i* the offshore intensity in the narrow sense is calculated as

$$OI1_i^{narrow} = \frac{imported\ input\ purchases\ of\ service\ or\ good\ i\ by\ sector\ i}{total\ non - energy\ inputs\ used\ by\ sector\ i},$$

while the wide indicator is defined as

$$OI1_j^{wide} = \sum_j \frac{imported\ input\ purchases\ of\ service\ or\ good\ j\ by\ sector\ i}{total\ non - energy\ inputs\ used\ by\ sector\ i}$$

A closely related indicator that largely follows the concept proposed by Feenstra and Hanson (1996, 1999) measures offshoring as the share of imported intermediate inputs in gross output. Offshoring is then reflected in the foreign content of domestic production. Again, a wide and a narrow indicator can be distinguished between. Formally, the two indicators are defined as

$$OI2_i^{narrow} = \frac{imported\ input\ purchases\ of\ service\ or\ good\ i\ by\ sector\ i}{output\ of\ sector\ i},$$

$$OI2_j^{wide} = \sum_j \frac{imported\ input\ purchases\ of\ service\ or\ good\ j\ by\ sector\ i}{output\ of\ sector\ i}$$

Existing data sources sometimes do not provide a direct measure of imported inputs. In that case the value has to be approximated. Feenstra and Hanson (1996, 1999) do so by multiplying the purchases of an input *j* by the import share in total absorption of the intermediate. Hence, the imported input purchases of service or good *j* by sector *i* are then measured as

$$[input\ purchases\ of\ service\ or\ good\ j\ by\ sector\ i] * \left[\frac{imports\ of\ service\ or\ good\ j}{consumption\ of\ service\ or\ good\ j}\right]$$

where consumption is production of service or good *j* plus imports minus exports. Hence the approximation embodies the assumption that the import share for an input *j* is constant across sectors. Clearly then, the direct measure should be preferred whenever available.

Offshoring is not a homogenous phenomenon but can and should be broken up along several dimensions. First, one may distinguish between material and service offshoring. The (wide) offshoring indicator can be used to construct distinct measures of the two types of offshoring by restricting the considered imported input purchases to either services or material inputs. Notice that service (material) offshoring is not limited to the service (manufacturing) sector. A manufacturing (service sector) firm can well import service (material) inputs. For instance, a car manufacturer could purchase accounting services from a foreign-based company.

Second, offshoring locations can be differentiated among in the analysis. In particular, offshoring to developing countries may have different effects than offshoring to developed regions. Since a breakdown of imported intermediate inputs by geographic region is typically not available, proxies of offshoring to different country groups can be calculated by assuming that the country distribution of imports in industry *i* is the same for intermediate inputs as it is for final products (cf. Ekholm and Hakkala, 2006[78]).

Discussion

The offshoring indicators described above have been used in numerous studies and can be considered as a rigorous approach to measure offshoring in the absence of more direct data. Nevertheless, a number of potential shortcomings have to be kept in mind. First, an increase in the indicator does not necessarily document offshoring in the sense the term was defined in Section II.2. In particular, imports of an intermediate good may not be associated with a relocation of production abroad. The value of offshoring is then overestimated. Second, the measure underestimates the actual offshoring values since import prices of intermediates are generally lower compared to the costs of purchasing them domestically. Third, total non-energy inputs, as used in the denominator of the indicator originally proposed by Feenstra and Hanson, do not include self-produced inputs.

Potential Offshoring

Brief Description

An empirical assessment of offshoring might not only consider the present magnitude of the phenomenon but also the *potential* employment effects. In this regard, studies for (selected) OECD countries by van Welsum and Reif (2005)[79] and van Welsum and Vickory (2005, 2006)[80]

[78] Ekholm, K. and Hakkala, K. (2006), "The Effect of Offshoring on Labour Demand: Evidence from Sweden," *CEPR Discussion Papers* 5648.
[79] Van Welsum, D. and Reif, X. (2005b), "Potential Offshoring: Evidence from Selected OECD Countries", *Brookings Trade Forum*, 165-194.
[80] Van Welsum, D., and Vickery, G. (2005), "Potential offshoring of ICT-intensive using occupations", *DSTI Information Economy Working Paper*, DSTI/ICCP/IE(2004)19/FINAL, OECD, Paris.
Van Welsum, D. and Vickory, G. (2006), "The share of employment potentially affected by offshoring – an empirical investigation", OECD Working Party on the Information Economy Report DSTI / ICCP / IE (2005) 8, Paris.

are noteworthy. The authors identify core features of jobs that are in principle "offshorable" and provide an estimate of the total number of "offshorable" jobs.

Van Welsum and Vickory (2005) suggest that as much as 20%of total employment could potentially be affected by international sourcing of IT and ICT-enabled services. The choice of occupations that are potentially offshorable is guided by the following four criteria ("offshorability attributes"):

- High usage-intensity of ICTs,
- output can (electronically) transmitted with the help of ICT,
- work has a high "codified knowledge" content and
- requires no face-to-face contact.

Discussion

While the approach is interesting and not limited to single countries, the present study will concentrate on the *de facto* prevalence of offshoring and its employment effects. And in reality, as pointed out by the OECD (2007, p.55), "only a small percentage of occupations classified as potentially offshorable are in fact offshored, and equally a small percentage of jobs classified as non-offshorable are in fact offshored." The latter case may arise when an occupation is generally not offshorable but the company itself (and hence the job as well) is offshored. Thus, for analyzing the actual magnitude of the offshoring phenomenon, the distinction between offshorable and non-offshorable jobs is hardly of any practical use.

II.4.3 Summary

In this section, we have reviewed several potential offshoring indicators. Arguably the most promising approach in the context of our study has been suggested by Feenstra and Hanson (1996, 1999). They measure offshoring as the fraction of imported intermediates in total inputs, an indicator that can be constructed from input-output tables. Importantly, harmonized input-output tables are provided by the OECD. Hence, data are sufficiently comparable across countries.

Proxies for offshoring to different countries can be calculated by assuming that imports of final and intermediate goods are similar in terms of the distribution of source countries. The sectoral breakdown of input-output tables also permits the construction of separate indices for service and material offshoring. For instance, service offshoring can be measured as the share of imported services in total inputs.

II.5 Empirical Analysis

In the previous sections we have reviewed the theoretical effects of offshoring on employment. Having also discussed how to measure offshoring, we are now in a position to put the theory to the data. The empirical analysis will focus on the largest EU economy, Germany, although the methods described can be applied to other countries as well. In particular, comparable data required to perform similar empirical analyses for other European countries are readily available.

We begin with a detailed overview of the outsourcing phenomenon in Germany. The evolution of outsourcing over time is computed and reported for a large number of service and manufacturing sectors. Next, the association of the observed rise in offshoring with technological change and the introduction of ICT is examined. We then turn to the labor market effects of offshoring and examine the association of changes in offshoring and employment at the industry-level. Finally, labor demand equations which incorporate offshoring explicitly are estimated and the econometric issues involved are discussed in some detail.

II.5.1 General Trends in the Offshoring Intensity in Germany

As argued in Section II.4, the most appropriate way to measure international outsourcing is the intensity of imported intermediates. Based on input-output tables of the German Federal Statistical Office, we calculated the share of imported intermediates in total non-energy inputs for 46 sectors at the two-digit industry level, grouping these into manufacturing, private services and public services.[81] Moreover, the analysis distinguishes between offshoring in the narrow and the wide sense. Narrowly-defined offshoring takes into account only those inputs imported from the same two-digit industry abroad, while the wide offshoring indicator includes intermediate imports from all foreign sectors. Finally, separate indices for service and material offshoring are calculated. For Germany, comparable data exist for 1991 to 2000, and then again from 2000 to 2004. Figures II.3 to II.6 present weighted averages of offshoring indicators over time for the three sector groupings and for the two types of offshoring.[82]

Figure II.3 depicts the narrow indicator of offshoring. For all three sectors considered there is a clear upward trend during the 1990s. Growth rates were considerably higher in private and public services, rising by 162 and 222 respectively per cent, respectively, from 1991 to 2000; for manufacturing the increase was 34.5%(from a much higher base). The second data series, ranging from 2000 to 2004, exhibits no such clear-cut trend, for public services the offshoring

[81] The manufacturing sector consists of the NACE sectors 15 to 37 while the service sector comprises NACE sectors 50 to 93. Sectors 50 to 74 are classified as private services.
[82] The share of an industry's total inputs is used as the weighting factor.

intensity even decreases somewhat. Figure II.3 also illustrates that while the service sector has been catching up, at least in the previous decade, offshoring remains more important in manufacturing. For 2004, the share of intermediates imported from the same industry abroad in total inputs was 0.119 for manufacturing, while for private services the narrow offshoring indicator had merely reached a third of that value at 0.038.

The wide offshoring measures the overall share of (non-energy) inputs of an industry that are imported from abroad. Figure II.4 illustrates that growth rates of offshoring are much less pronounced when the latter is measured using a wide rather than a narrow concept. Comparing Figures II.3 and II.4 suggests that most of the rapid development in offshoring is due to firms' shifting their core activities abroad. Nevertheless, the wide offshoring indicator also exhibits a clear upward trend in all sectors during the 1990s. The development is more dynamic in services but even in manufacturing the offshoring intensity has increased by almost 20%between 1991 and 2000. The wide measure also confirms the previous finding that despite of the strong growth rates in services, offshoring is still more prevalent in manufacturing. In 2004, about a quarter of all inputs used by German manufacturing industries was imported from abroad. For services the share of imported intermediates in total inputs amounted to just 12 per cent.

Finally, Figures II.5 and II.6 depict separately the trend in material and service offshoring. Over the 1990s the offshoring of services accelerated markedly in the service sector while limited in manufacturing. After the turn of the millennium the data indicate a trend reversal for public services while service offshoring was roughly constant in the private service sector and in manufacturing. The results for material offshoring point into the opposite direction. Here, growth rates were strongest for the manufacturing industries. Therefore, the results suggest that the general upward trend in offshoring was primarily driven by material offshoring in manufacturing industries, while for the service sector service offshoring appears responsible. This finding supports the hypothesis that the rise in offshoring is mainly due to firms shifting their core activities abroad.

Differences in offshoring intensity exist not only between manufacturing and services, but also within the two sectors. Tables II.2 to II.5 document the development of all four measures of offshoring at the two-digit sector level for 1991 to 2000. Most industries have experienced significant increases in the intensity of offshoring. In sectors like `apparel' or `research and development', growth rates of the indicators were 100%or more over the ten year period considered. However, many services remain non-tradable. Accordingly, offshoring, at least when defined narrowly, does not play any role in, for instance, the hotel and restaurant sector. Likewise, even in manufacturing a few industries, e.g. `printing and publishing', show no upward trend in their outsourcing intensity during the 1990s. It is precisely this variation across industries that we will use in the following to analyze the link between offshoring and employment.

Figure II.3: Offshoring (narrow), Germany, 1991 – 2004

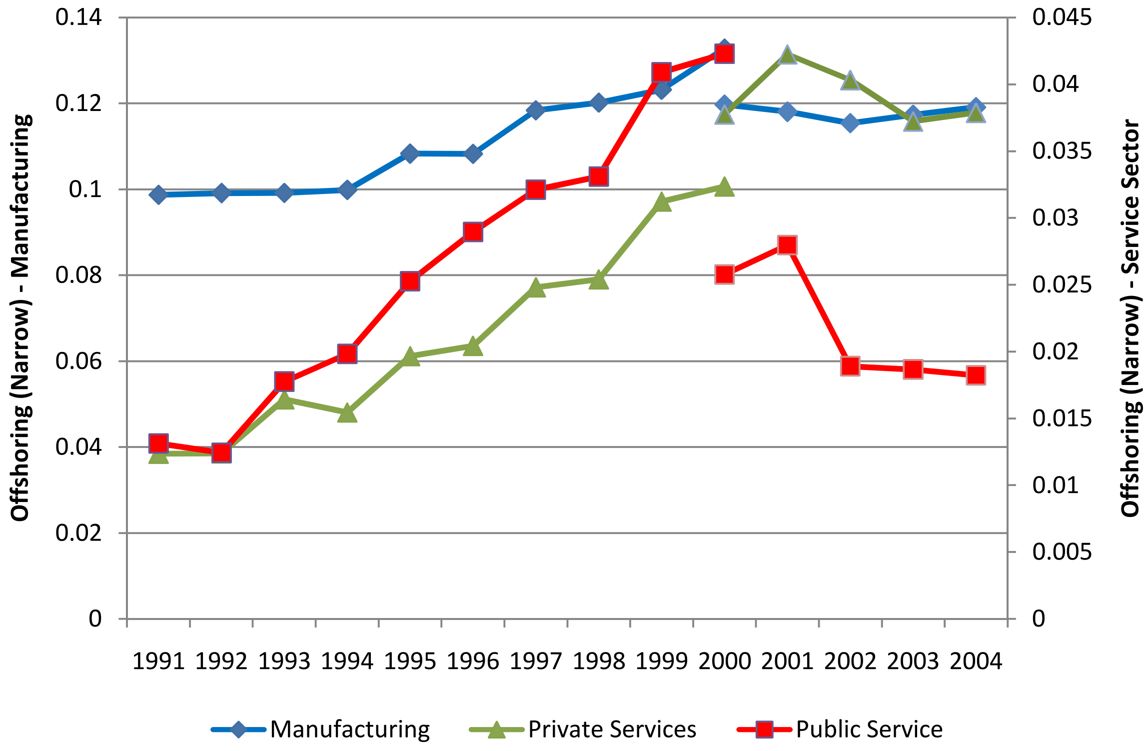


Figure II.4: Offshoring (wide), Germany, 1991 – 2004

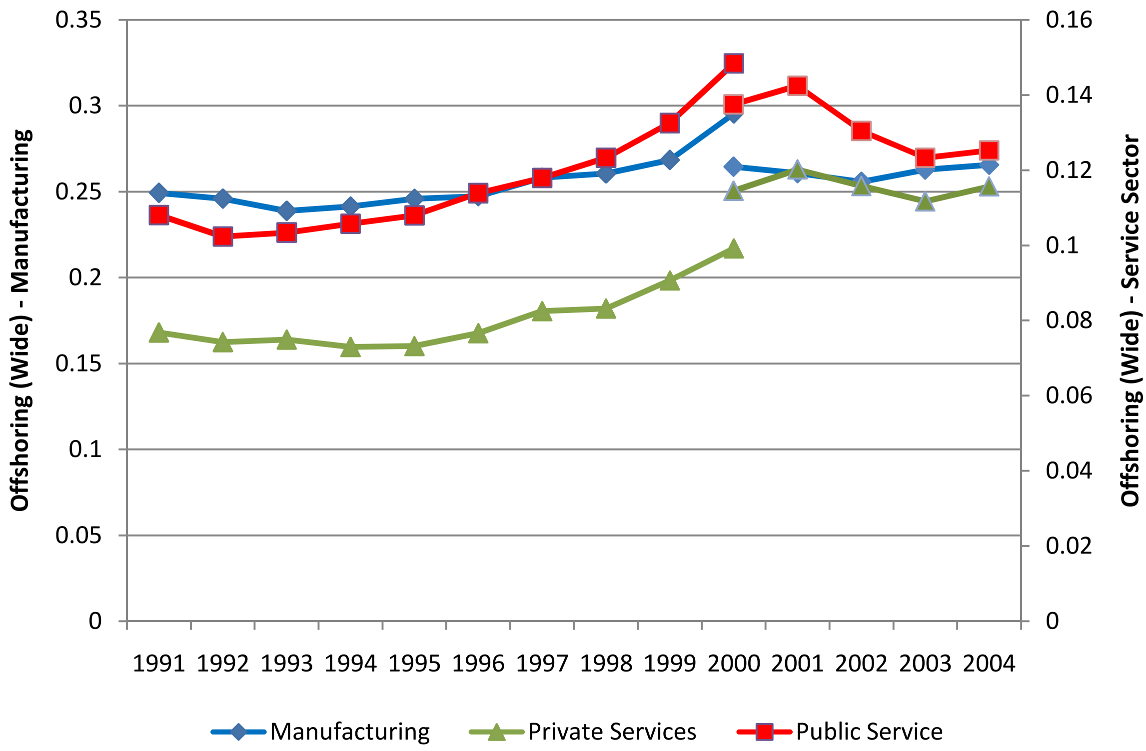


Figure II.5: Service offshoring, Germany, 1991 – 2004

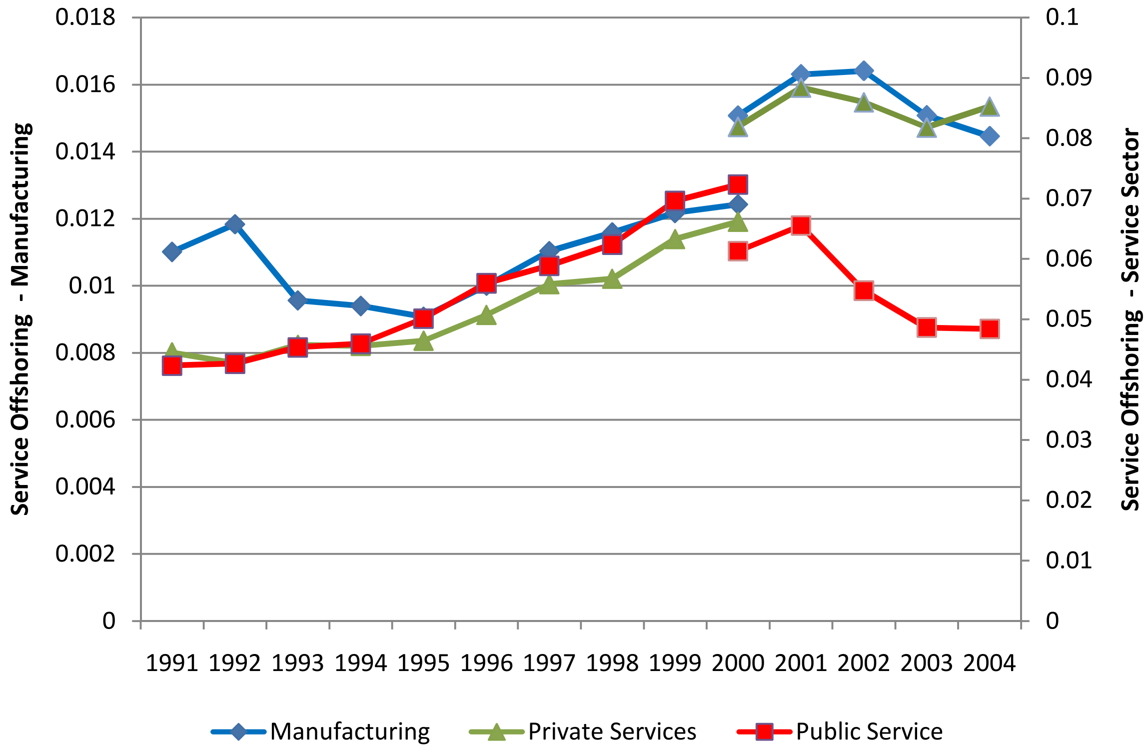


Figure II.6: Material offshoring, Germany, 1991 – 2004

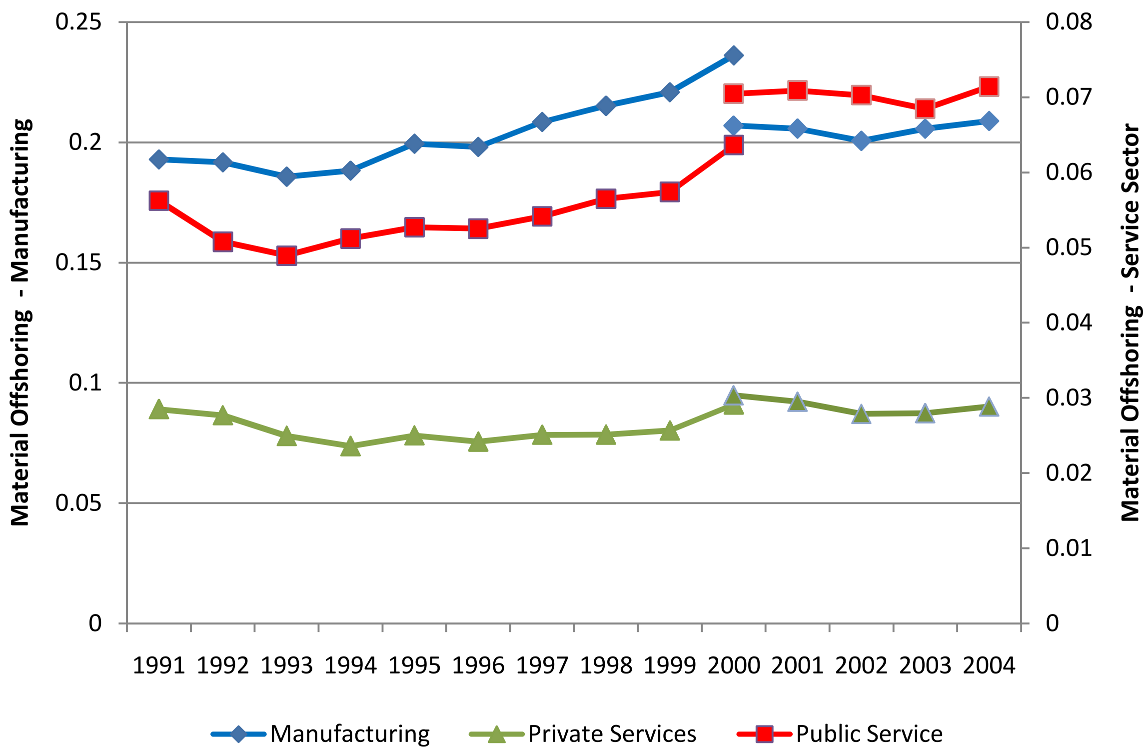


Table II.2: Level and evolution of narrow offshoring indicator at the two-digit industry level, Germany, 1991 to 2000

Sector	Mean	Min	Max	Δ (in %) 1991 – 2000
All Manufacturing (15 - 37), weighted average	0.111	0.099	0.133	34.50
Foods Products and Beverages	0.052	0.047	0.059	1.81
Tobacco Products	0.010	0.002	0.032	535.72
Textiles	0.124	0.085	0.154	80.92
Wearing Apparel, Dressing and Dying of Fur	0.211	0.114	0.320	109.22
Leather, Leather Products and Footwear	0.268	0.170	0.363	108.48
Wood and Products of Wood and Cork	0.076	0.069	0.084	-7.11
Pulp. Paper and Paper Products	0.241	0.183	0.269	18.79
Printing and Publishing	0.032	0.029	0.035	-6.98
Coke, Refined Petroleum and Nuclear Fuel	0.064	0.046	0.090	-11.33
Chemicals and Chemical Products	0.180	0.149	0.237	51.79
Rubber and Plastics Products	0.013	0.007	0.018	85.67
Other Non-Metallic Mineral Products	0.042	0.040	0.045	-4.64
Basic Metals	0.227	0.185	0.254	30.00
Fabricated Metals Products	0.024	0.020	0.028	28.62
Machinery, and Equipment, NEC.	0.089	0.078	0.099	15.94
Office, Accounting and Computing Machinery	0.230	0.144	0.317	95.63
Electrical Machinery and Apparatus, NEC	0.083	0.071	0.103	32.49
Radio, TV and Communication Equipment	0.264	0.236	0.324	30.80
Medical Precision and Optical Instruments	0.072	0.060	0.080	-0.66
Motor Vehicles, Trailers and Semi-Trailers	0.132	0.114	0.178	14.42
Other Transport Equipment	0.419	0.331	0.574	60.10
Manufacturing NEC	0.102	0.083	0.139	56.26
Recycling	0.000	0.000	0.000	0.00
All Private Services (50–74), weighted average	0.021	0.012	0.032	161.53
Sale, Maintenance and Repair of Motor Vehicles; Retail Sale of Fuel	0.000	0.000	0.000	0.00
Wholesale, Trade & Commission	0.079	0.030	0.130	271.91
Retail Trade	0.000	0.000	0.000	0.00
Hotels and Restaurants	0.000	0.000	0.000	-73.33
Land Transport; Transport via Pipelines	0.012	0.003	0.026	680.58
Water Transport	0.001	0.000	0.004	-96.72
Air Transport	0.000	0.000	0.000	-33.05
Supporting and Auxiliary Transport Activities	0.011	0.004	0.025	-79.59
Post and Telecommunications	0.186	0.145	0.228	-16.28
Financial Intermediations	0.002	0.001	0.003	196.55
Insurance and Pension Funding	0.002	0.000	0.005	-99.42
Activities Related to Financial Intermediation	0.004	0.000	0.017	-100.00
Real Estate Activities	0.015	0.013	0.021	39.65
Renting of Machinery and Equipment	0.007	0.000	0.018	-100.00
Computer and Related Activities	0.052	0.003	0.120	3672.10
Research and Development	0.021	0.011	0.036	171.51
Other Business Activities	0.038	0.013	0.062	315.09
All Public Services (75 – 93), weighted average	0.027	0.012	0.042	222.48
Public Administration and Defense; Compulsory Social Security	0.017	0.008	0.025	163.35
Education	0.000	0.000	0.000	0.00
Health and Social Work	0.000	0.000	0.000	0.00
Sewage and refuse disposal, sanitation and similar activities	0.036	0.026	0.047	70.64
Activities of membership organizations n.e.c.	0.000	0.000	0.000	0.00
Recreational, cultural and sporting activities	0.125	0.059	0.192	198.08
Other service activities	0.024	0.003	0.047	1708.50

Table II.3: Level and evolution of wide offshoring indicator at the two-digit industry level, Germany, 1991 to 2000

Sector	Mean	Min	Max	Δ (in %) 1991 – 2000
All Manufacturing (15 - 37), weighted average	0.255	0.2388	0.2955	18.50
Foods Products and Beverages	0.173	0.164	0.184	-6.20
Tobacco Products	0.214	0.146	0.270	39.82
Textiles	0.328	0.273	0.396	44.66
Wearing Apparel, Dressing and Dying of Fur	0.434	0.321	0.547	57.32
Leather, Leather Products and Footwear	0.365	0.289	0.461	56.35
Wood and Products of Wood and Cork	0.155	0.142	0.173	7.69
Pulp. Paper and Paper Products	0.351	0.295	0.423	23.68
Printing and Publishing	0.133	0.1221	0.146	-0.50
Coke, Refined Petroleum and Nuclear Fuel	0.672	0.601	0.872	36.18
Chemicals and Chemical Products	0.297	0.264	0.381	39.35
Rubber and Plastics Products	0.319	0.293	0.373	14.81
Other Non-Metallic Mineral Products	0.153	0.137	0.193	21.53
Basic Metals	0.356	0.308	0.422	29.29
Fabricated Metals Products	0.174	0.156	0.197	15.09
Machinery, and Equipment, NEC.	0.210	0.194	0.239	16.50
Office, Accounting and Computing Machinery	0.421	0.297	0.547	57.39
Electrical Machinery and Apparatus, NEC	0.172	0.148	0.201	22.14
Radio, TV and Communication Equipment	0.355	0.323	0.415	19.19
Medical Precision and Optical Instruments	0.194	0.177	0.226	12.61
Motor Vehicles, Trailers and Semi-Trailers	0.255	0.237	0.298	12.00
Other Transport Equipment	0.506	0.421	0.645	44.12
Manufacturing NEC	0.279	0.256	0.319	14.31
Recycling	0.109	0.096	0.127	-10.43
All Private Services (50–74), weighted average	0.080	0.073	0.099	29.16
Sale, Maintenance and Repair of Motor Vehicles; Retail Sale of Fuel	0.099	0.085	0.127	-2.91
Wholesale, Trade & Commission	0.120	0.075	0.170	103.83
Retail Trade	0.048	0.037	0.066	-22.09
Hotels and Restaurants	0.121	0.113	0.129	-5.18
Land Transport; Transport via Pipelines	0.058	0.045	0.072	15.05
Water Transport	0.598	0.499	0.737	28.32
Air Transport	0.423	0.374	0.497	21.50
Supporting and Auxiliary Transport Activities	0.024	0.016	0.042	-54.07
Post and Telecommunications	0.229	0.201	0.269	-5.40
Financial Intermediations	0.049	0.043	0.062	27.00
Insurance and Pension Funding	0.048	0.040	0.059	-4.80
Activities Related to Financial Intermediation	0.193	0.073	0.291	144.89
Real Estate Activities	0.031	0.019	0.048	-44.00
Renting of Machinery and Equipment	0.013	0.004	0.028	-79.96
Computer and Related Activities	0.102	0.037	0.185	324.75
Research and Development	0.091	0.059	0.131	100.89
Other Business Activities	0.079	0.052	0.110	63.81
All Public Services (75 – 93), weighted average	0.116	0.102	0.148	37.29
Public Administration and Defense; Compulsory Social Security	0.133	0.106	0.165	35.04
Education	0.112	0.098	0.144	28.31
Health and Social Work	0.106	0.092	0.127	16.26
Sewage and refuse disposal, sanitation and similar activities	0.104	0.085	0.120	16.37
Activities of membership organizations n.e.c.	0.046	0.033	0.060	-7.87
Recreational, cultural and sporting activities	0.160	0.106	0.228	107.13
Other service activities	0.058	0.041	0.083	75.60

Table II.4: Level and evolution of service offshoring indicator at the two-digit industry level, Germany, 1991 to 2000

Sector	Mean	Min	Max	Δ (in %) 1991 – 2000
All Manufacturing (15 - 37), weighted average	0.011	0.009	0.012	12.86
Foods Products and Beverages	0.005	0.004	0.009	-34.10
Tobacco Products	0.010	0.006	0.013	-4.52
Textiles	0.008	0.006	0.010	-24.37
Wearing Apparel, Dressing and Dying of Fur	0.005	0.003	0.008	-50.85
Leather, Leather Products and Footwear	0.007	0.003	0.013	-65.09
Wood and Products of Wood and Cork	0.011	0.008	0.013	13.34
Pulp. Paper and Paper Products	0.010	0.008	0.012	-13.72
Printing and Publishing	0.010	0.008	0.013	-21.46
Coke, Refined Petroleum and Nuclear Fuel	0.006	0.006	0.007	-60.46
Chemicals and Chemical Products	0.037	0.027	0.051	80.24
Rubber and Plastics Products	0.011	0.009	0.012	22.90
Other Non-Metallic Mineral Products	0.020	0.019	0.023	-8.37
Basic Metals	0.009	0.008	0.011	-6.58
Fabricated Metals Products	0.008	0.007	0.010	-1.26
Machinery, and Equipment, NEC.	0.009	0.007	0.011	0.74
Office, Accounting and Computing Machinery	0.041	0.019	0.071	264.04
Electrical Machinery and Apparatus, NEC	0.007	0.005	0.010	22.94
Radio, TV and Communication Equipment	0.006	0.004	0.008	-21.55
Medical Precision and Optical Instruments	0.009	0.007	0.011	-6.05
Motor Vehicles, Trailers and Semi-Trailers	0.006	0.004	0.007	-3.99
Other Transport Equipment	0.006	0.005	0.007	8.42
Manufacturing NEC	0.005	0.002	0.010	-71.02
Recycling	0.011	0.008	0.013	18.68
All Private Services (50–74), weighted average	0.052	0.043	0.066	48.64
Sale, Maintenance and Repair of Motor Vehicles; Retail Sale of Fuel	0.006	0.0023	0.013	-75.26
Wholesale, Trade & Commission	0.102	0.054	0.153	153.59
Retail Trade	0.012	0.004	0.027	-83.46
Hotels and Restaurants	0.005	0.003	0.010	-57.62
Land Transport; Transport via Pipelines	0.024	0.012	0.034	53.10
Water Transport	0.568	0.466	0.707	30.11
Air Transport	0.192	0.173	0.235	5.15
Supporting and Auxiliary Transport Activities	0.018	0.011	0.034	-61.85
Post and Telecommunications	0.199	0.162	0.242	-13.33
Financial Intermediations	0.048	0.042	0.060	26.28
Insurance and Pension Funding	0.043	0.035	0.053	-7.28
Activities Related to Financial Intermediation	0.192	0.071	0.290	145.78
Real Estate Activities	0.023	0.015	0.035	-36.56
Renting of Machinery and Equipment	0.010	0.001	0.024	-91.70
Computer and Related Activities	0.074	0.021	0.146	594.05
Research and Development	0.048	0.025	0.074	197.99
Other Business Activities	0.052	0.027	0.077	120.00
All Public Services (75 – 93), weighted average	0.055	0.042	0.072	70.80
Public Administration and Defense; Compulsory Social Security	0.075	0.054	0.092	58.30
Education	0.052	0.043	0.058	10.40
Health and Social Work	0.009	0.006	0.012	-35.16
Sewage and refuse disposal, sanitation and similar activities	0.058	0.046	0.072	41.91
Activities of membership organizations n.e.c.	0.014	0.008	0.025	-57.87
Recreational, cultural and sporting activities	0.138	0.075	0.204	152.71
Other service activities	0.030	0.013	0.050	262.42

Table II.5: Level and evolution of material offshoring indicator at the two-digit industry level, Germany, 1991 to 2000

Sector	Mean	Min	Max	Δ (in %) 1991 – 2000
All Manufacturing (15 - 37), weighted average	0.204	0.186	0.236	22.46
Foods Products and Beverages	0.071	0.063	0.079	12.21
Tobacco Products	0.045	0.033	0.061	22.74
Textiles	0.270	0.219	0.329	49.76
Wearing Apparel, Dressing and Dying of Fur	0.425	0.312	0.538	59.41
Leather, Leather Products and Footwear	0.355	0.272	0.453	62.44
Wood and Products of Wood and Cork	0.128	0.118	0.137	1.19
Pulp. Paper and Paper Products	0.321	0.262	0.358	15.59
Printing and Publishing	0.123	0.112	0.132	-0.06
Coke, Refined Petroleum and Nuclear Fuel	0.088	0.066	0.107	-29.40
Chemicals and Chemical Products	0.248	0.220	0.305	30.28
Rubber and Plastics Products	0.290	0.268	0.342	18.14
Other Non-Metallic Mineral Products	0.077	0.071	0.085	2.31
Basic Metals	0.275	0.234	0.311	26.17
Fabricated Metals Products	0.163	0.145	0.178	12.08
Machinery, and Equipment, NEC.	0.199	0.185	0.225	16.12
Office, Accounting and Computing Machinery	0.380	0.275	0.475	45.11
Electrical Machinery and Apparatus, NEC	0.163	0.140	0.189	21.11
Radio, TV and Communication Equipment	0.348	0.318	0.407	19.71
Medical Precision and Optical Instruments	0.184	0.169	0.214	12.91
Motor Vehicles, Trailers and Semi-Trailers	0.248	0.229	0.290	11.63
Other Transport Equipment	0.498	0.413	0.634	44.18
Manufacturing NEC	0.269	0.249	0.309	17.22
Recycling	0.094	0.082	0.114	-20.79
All Private Services (50–74), weighted average	0.026	0.024	0.029	2.18
Sale, Maintenance and Repair of Motor Vehicles; Retail Sale of Fuel	0.090	0.081	0.115	4.14
Wholesale, Trade & Commission	0.017	0.015	0.022	-19.33
Retail Trade	0.033	0.029	0.037	3.32
Hotels and Restaurants	0.099	0.091	0.111	1.57
Land Transport; Transport via Pipelines	0.033	0.027	0.039	-4.62
Water Transport	0.029	0.024	0.037	6.12
Air Transport	0.231	0.192	0.315	33.48
Supporting and Auxiliary Transport Activities	0.005	0.003	0.008	-22.55
Post and Telecommunications	0.028	0.019	0.040	45.23
Financial Intermediations	0.001	0.001	0.002	19.79
Insurance and Pension Funding	0.004	0.003	0.005	5.48
Activities Related to Financial Intermediation	0.001	0.001	0.001	35.63
Real Estate Activities	0.003	0.002	0.006	-21.41
Renting of Machinery and Equipment	0.003	0.002	0.004	-9.57
Computer and Related Activities	0.027	0.010	0.038	80.13
Research and Development	0.042	0.030	0.054	38.52
Other Business Activities	0.026	0.023	0.023	-0.60
All Public Services (75 – 93), weighted average	0.054	0.049	0.064	13.13
Public Administration and Defense; Compulsory Social Security	0.049	0.041	0.057	7.12
Education	0.048	0.038	0.059	30.79
Health and Social Work	0.087	0.071	0.105	22.45
Sewage & Refuse Disposal, Sanitation, etc.	0.044	0.037	0.050	-7.00
Activities of Member Organizations nec	0.026	0.022	0.032	10.07
Recreational, Cultural and Sporting Activities	0.019	0.014	0.025	-10.03
Other Service Activities	0.028	0.024	0.032	0.24

II.5.2 Offshoring and the ICT Expenditures: Sectoral Evidence

Having discussed the rise of offshoring in Germany in some detail, we now turn to the question of whether or not this development can be attributed to the rapid advances in information and communication technologies.

Both in the academic and the public discussion, ICT is typically seen as a main driver of offshoring that promotes the diffusion of production stages across national boundaries. In particular, ICT enhances the coordination of tasks performed at different locations. It also facilitates the transmission of instructions and permits the (electronic) transmission of output. Consequently, ICT allows for a finer international division of labor and enables firms to take advantage of international cost differences. Arguably, ICT should be especially important for service offshoring but can also contribute to the increase in material offshoring documented in the previous section. Commonly cited examples for the importance of ICT for service offshoring are research and consultancy services (ICT-enabled business services). While until recently those services were considered to be largely impervious to international competition, they can now be carried out remotely via the Internet and tele- and video-conferencing.

In the following, we examine this "conventional wisdom" and examine the association of ICT with offshoring. Given that we lack a structural model that could guide the empirical analysis and in the light of the shortcomings of our offshoring and technology measures, the evidence presented in the following is far from conclusive and should be considered preliminary. All the same, it is consistent with causality running from technical change to offshoring.

Table II.6 displays simple sector-level correlations between the level of ICT investment in an industry (relative to its gross output)[83] and the four offshoring indicators. Correlations are presented separately for manufacturing and services and are based on panel data for 1991 to 2000. The correlation between ICT investment and narrow offshoring is positive and (statistically) significantly different from zero in both sectoral grouping. For service offshoring the correlation coefficients are also positive in sign even though it is barely significant for the service sector (p-value of 0.11). The correlation coefficients between ICT investment and wide offshoring tend to zero for both sectors considered, while they pull into different directions for material offshoring. For the manufacturing sector we do find the expected positive sign. However, the correlation is negative for services.

In order to account for industry-specific (but time-invariant) effects we proceed by estimating simple fixed effects regressions. The four offshoring indicators are one by one chosen as the

[83] See Section I.5 for a detailed discussion of ICT indicators. The data are taken from the EU KLEMS data base. While the ICT indicator is in principle available at the two-digit sector level, for a number of industries the variable can only be computed at a more aggregated level. For instance, for sectors 15 and 16 only data on the combined ICT investment of the two sectors is available; ICT investment (relative to gross output) is then taken to be identical in these two sectors. Similar problems exist with respect to the manufacturing sectors 17-19, 21-22, 27-28, 30-33, 34-35, 36-37 and the service sectors 60-63 and 71-74.

dependent variable and regressed on ICT investment. As before, we consider the manufacturing and the service sector separately. The upper panel of Table II.7 shows that ICT investment enters with a positive sign and is highly statistically significant at all conventional significance levels. This is true for both sectors and all four offshoring indicators. In the lower panel, we report the results of a regression in which year dummies are used to capture time trends in the offshoring intensity that are common across industries. In all but one regression the coefficient on the ICT variable remains positive in sign. However, once time dummies are included the effect of ICT on offshoring is rendered statistically insignificant in the manufacturing sector. For services, on the contrary, we still find a positive and statistically significant association of ICT investment with narrow, wide, and service offshoring. When interpreting the results of the regression with time dummies, one has to bear in mind that technological progress evolves over time. Hence, a simple common linear time trend is positively correlated with ICT investment and the year dummies themselves can be considered as a proxy for technological development. Therefore, it is not surprising that the association of ICT investment with offshoring changes quite dramatically once year dummies are included into the analysis.

In summary, a first glance at the data suggests that the rise in offshoring is indeed associated with the extent of the ICT revolution, as measured by the ratio of investment expenditures to gross output. Beyond any doubt, more work remains to be done to gain a more thorough understanding of the determinants of offshoring.

Table II.6: Correlations between the level of ICT investment (in percentage of gross output) and offshoring, Germany, 1991 to 2000

	Correlation between ICT Investment and			
	Offshoring (narrow)	Offshoring (wide)	Service offshoring	Material offshoring
Manufacturing	.214**	-.060	.209**	.191**
	(.001)	(.379)	(.002)	(.005)
Services	.503***	.025	.103	-.168*
	(.000)	(.698)	(.110)	(.009)

***, **, *: statistically significant at 1, 5, and 10 % level, respectively; p-values in parentheses; H_0: correlation coefficient is zero.
Number of observations: 220 (manufacturing) and 240 (service sector), respectively.
Industry-level panel-data for 1991 to 2000 is used for calculating the correlation coefficients.

Table II.7: Fixed effect regression results: offshoring and ICT, Germany, 1991-2000

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Manufacturing Sector				Service Sector			
Dep.Variable	Offshoring (narrow)	Offshoring (wide)	Service Offshoring	Material Offshoring	Offshoring (narrow)	Offshoring (wide)	Service Offshoring	Material Offshoring
I_{ICT} / Y	7.73***	10.76***	.650***	9.36***	.451***	.777***	.632***	.132***
	(1.576)	(1.849)	(.249)	(1.66)	(.133)	(.168)	(.151)	(.034)
R^2 (within)	.161	.210	.061	.227	.127	.113	.083	.046
Year Dummies	No	No	No	No	No	No	No	No
I_{ICT} / Y	.694	-2.55	.305	1.23	.297*	.417**	.375**	.027
	(1.17)	(2.11)	(.241)	(1.67)	(.153)	(.174)	(.158)	(.041)
R^2 (within)	.308	.471	.096	.386	.199	.207	.190	.177
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector Fixed Eff.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	220	220	220	220	240	240	240	240

***, **, *: statistically significant at 1, 5, and 10 % level, respectively; robust standard errors in parentheses

II.5.3 Establishing Simple Correlations between Employment and Offshoring

As a first step towards an evaluation of the employment effects we use industry-level data to correlate changes of the offshoring intensity with changes in employment. In particular, for each two-digit industry the relative change (in per cent) of offshoring between 1991 and 2000 is calculated. Likewise, using data from the EU KLEMS data base, the relative change in the number of employees is computed for the same time period. Since the general employment trend has been very different between the service and the manufacturing sector, correlation coefficients between the change in employment and the various offshoring indicators were calculated for the service sector and for manufacturing separately. The results are shown in Table II.8. Figures II.7 to II.14 depict the corresponding scatter plots between the changes in employment and the changes in offshoring.

Table II.8: Correlations between changes in employment and offshoring, Germany, 1991-2000

	Correlation between Change in Employment and Change in…			
	Offshoring (narrow)	Offshoring (wide)	Service offshoring	Material offshoring
Manufacturing Sector	-.209	-.824***	-.189	-.556*
	(.352)	(.000)	(.400)	(.072)
Service Sector	.382*	.264	.314	.053
	(.066)	(.212)	(.135)	(.806)

***, **, *: statistically significant at 1, 5, and 10 % level, respectively; p-values in parentheses; H_0: correlation coefficient is zero.
Number of observations: 22 (manufacturing) and 24 (service sector), respectively
Note: The correlation between narrow offshoring and employment in manufacturing turns statistically significant if only changes in narrow offshoring of at most 300%are considered. For the service sector the correlation is then rendered statistically insignificant.

The results show that the relationship between offshoring and employment differs widely between sectors, and depends on the type of indicator used. For manufacturing we consistently find that the relative changes in offshoring are negatively correlated with the change in employment, i.e. the higher the growth rate of the offshoring intensity of an industry the lower is domestic employment growth. The magnitude of the (negative) correlation was strongest for wide and for material offshoring, with coefficients of -.824 and -.556, respectively. The correlation coefficient was statistically significantly different from zero when the narrow indicator was used or service offshoring was considered.[84] The findings change markedly once the service sector is considered. Now all four correlation coefficients exhibit a positive sign even though only the correlation between the change in narrow offshoring and employment growth is statistically significant at the 10%level.

[84] Notice that the correlation between the growth rate of narrow offshoring and employment growth turned statistically significant once outliers (defined as observations with changes in the offshoring intensity of more than 300 per cent) had been excluded.

To summarize, simple industry-level correlation coefficients hint at negative employment effects of offshoring for the manufacturing sector. In contrast, weak evidence was found for a positive relation between offshoring and employment in services. In a next step, we turn to the estimation of labor demand equations to test for the employment effects of offshoring in a more formal way.

Figure II.7: Change in employment vs. change in offshoring (narrow), German manufacturing, 1991 to 2000

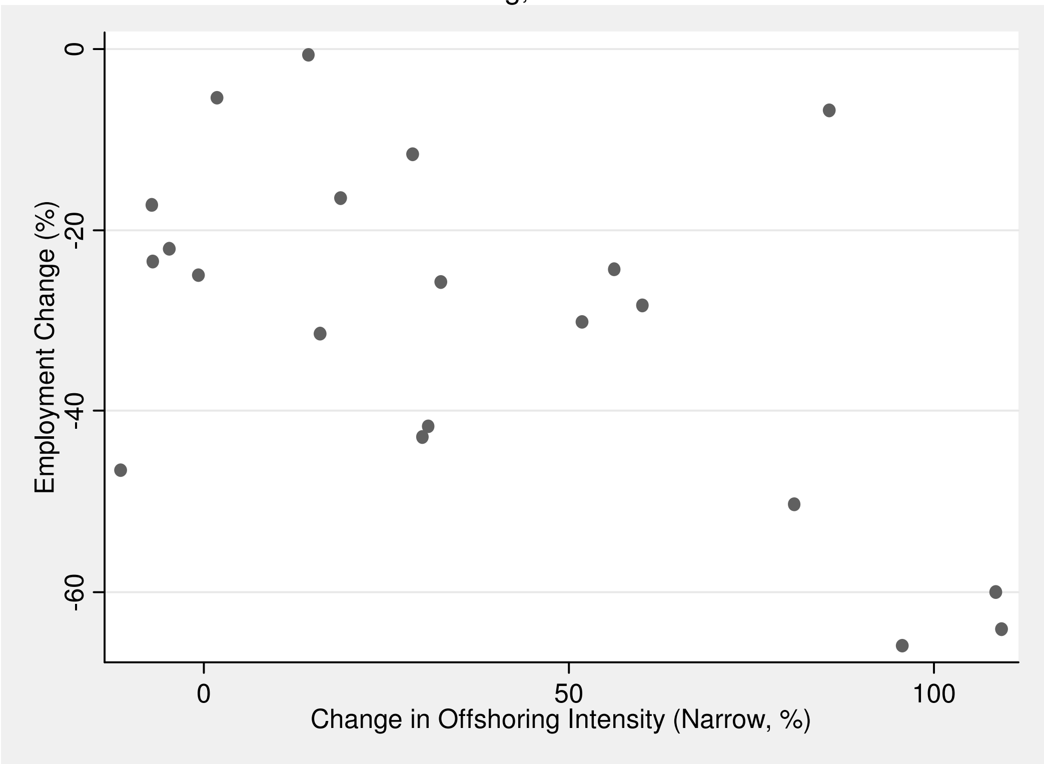


Figure II.8: Change in employment vs. change in offshoring (narrow), German services, 1991 to 2000

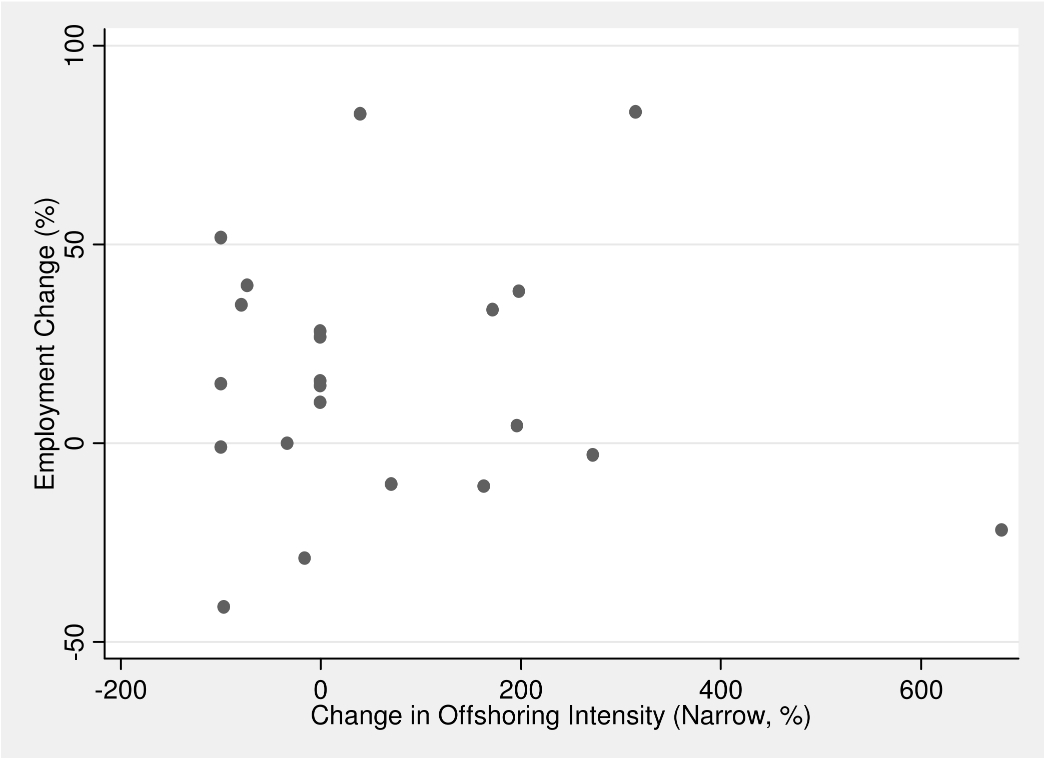


Figure II.9: Change in employment vs. change in offshoring (wide), German manufacturing, 1991 to 2000

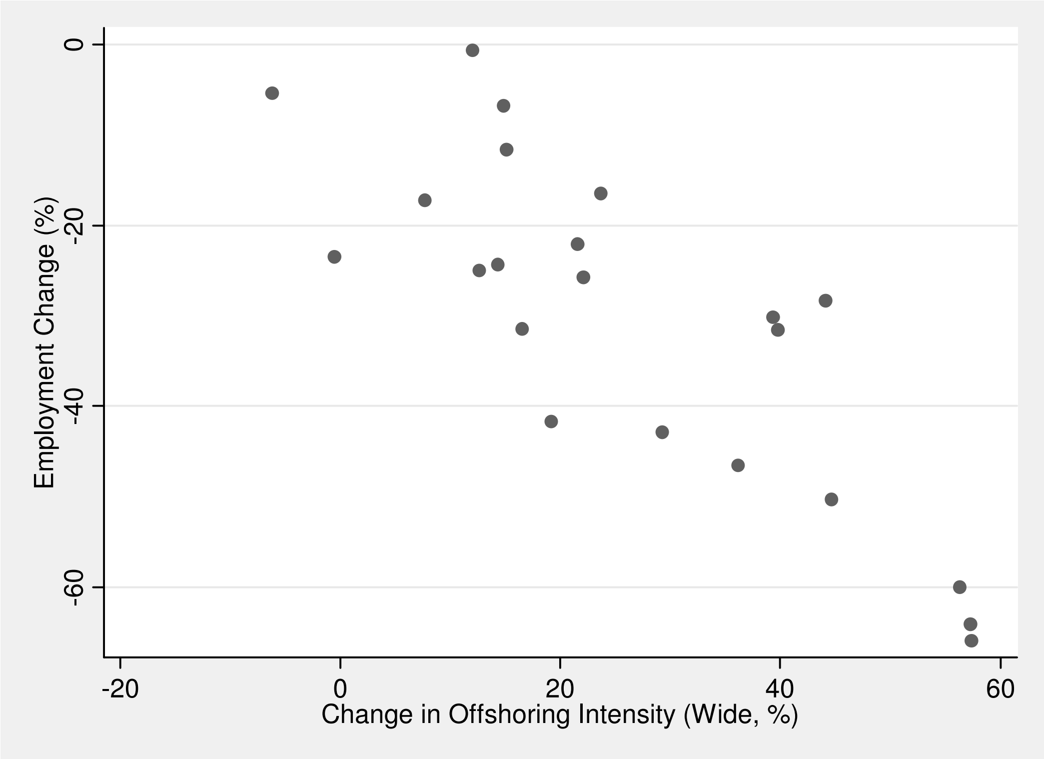


Figure II.10: Change in employment vs. change in offshoring (wide), German services, 1991 to 2000

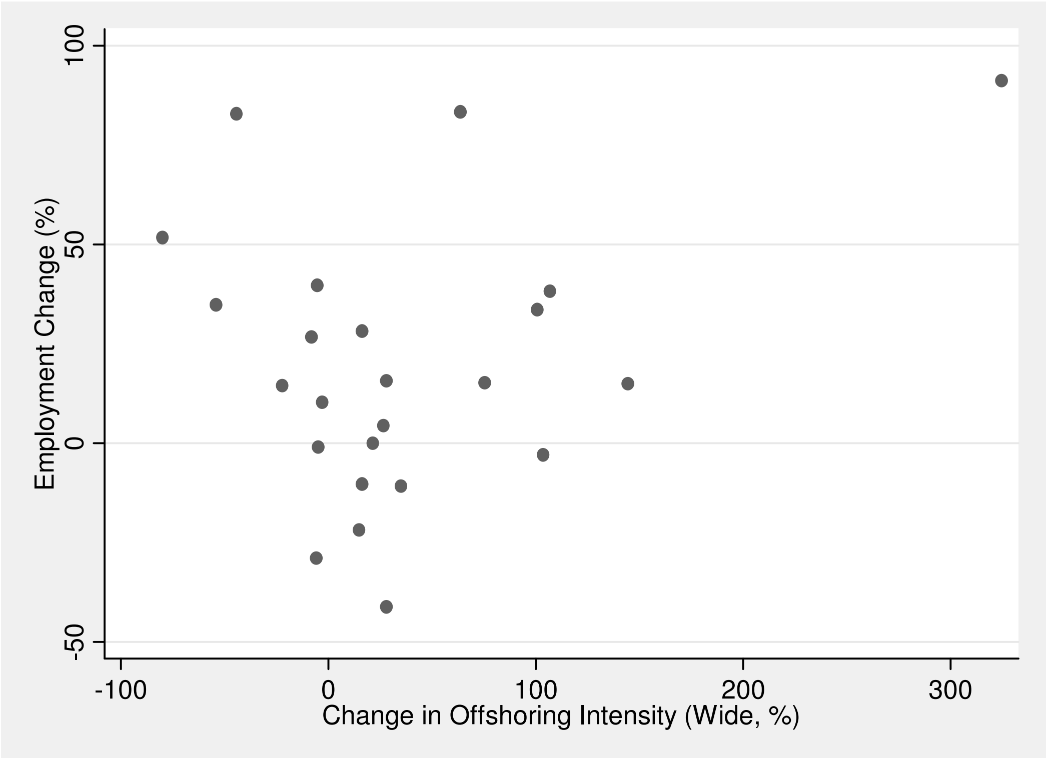


Figure II.11: Change in employment vs. change in service offshoring, German manufacturing, 1991 to 2000

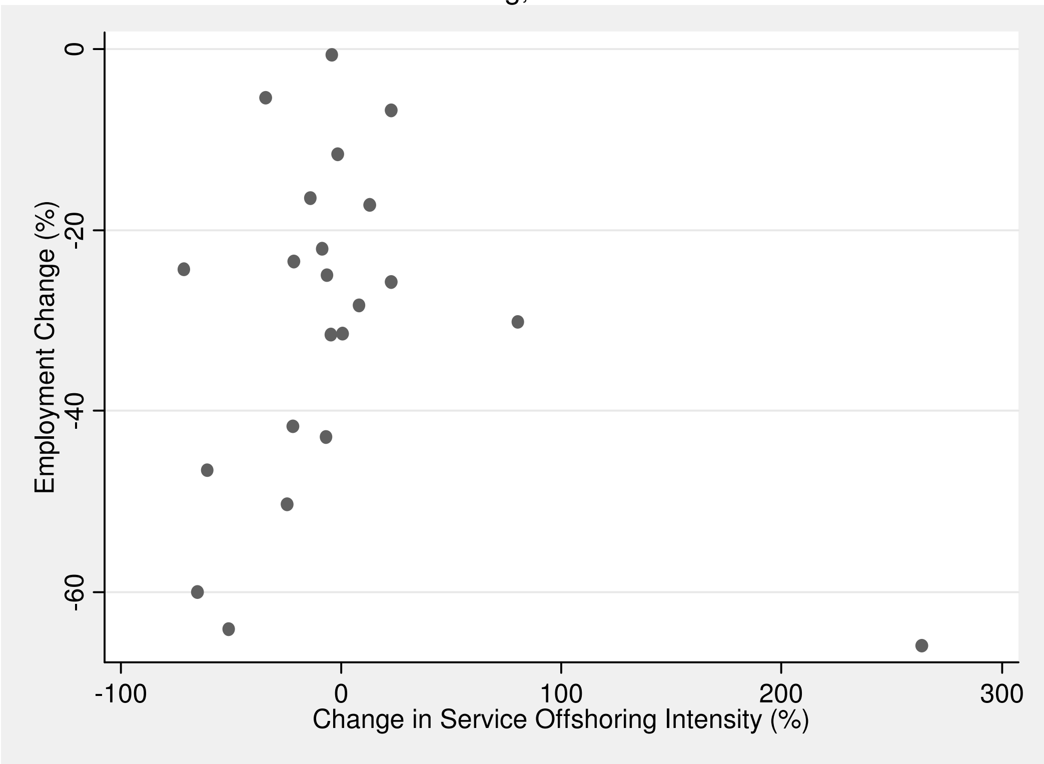


Figure II.12: Change in employment vs. change in service offshoring, German manufacturing, 1991 to 2000

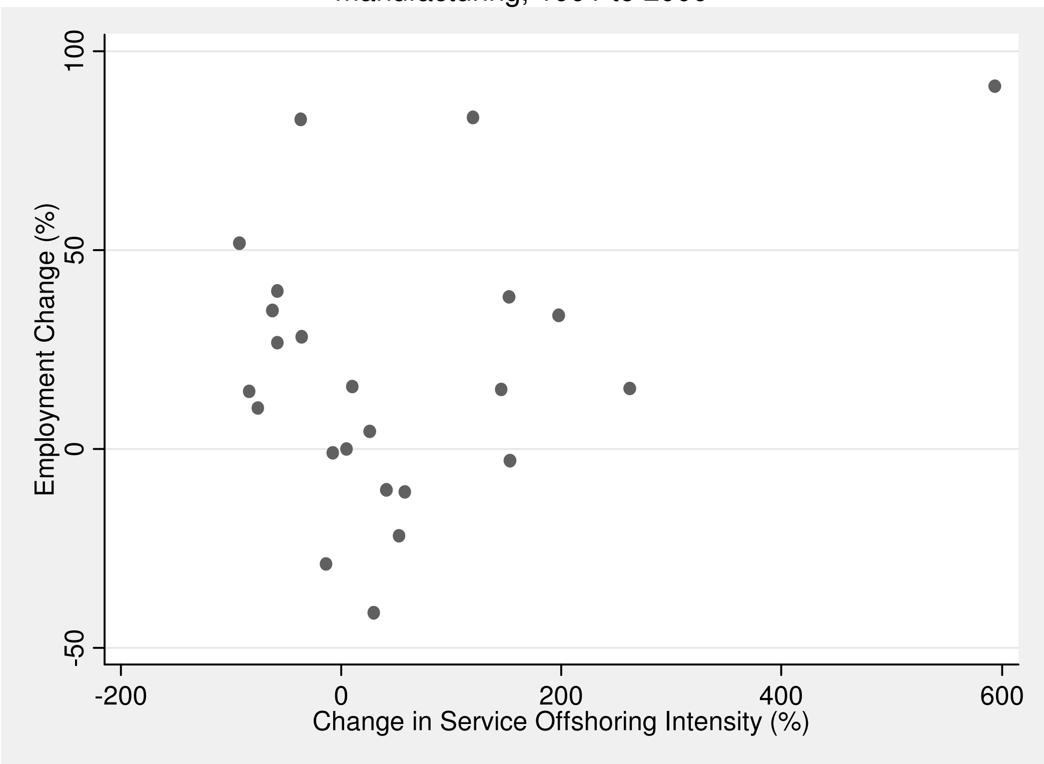


Figure II.13: Change in employment vs. change in material offshoring, German manufacturing, 1991 to 2000

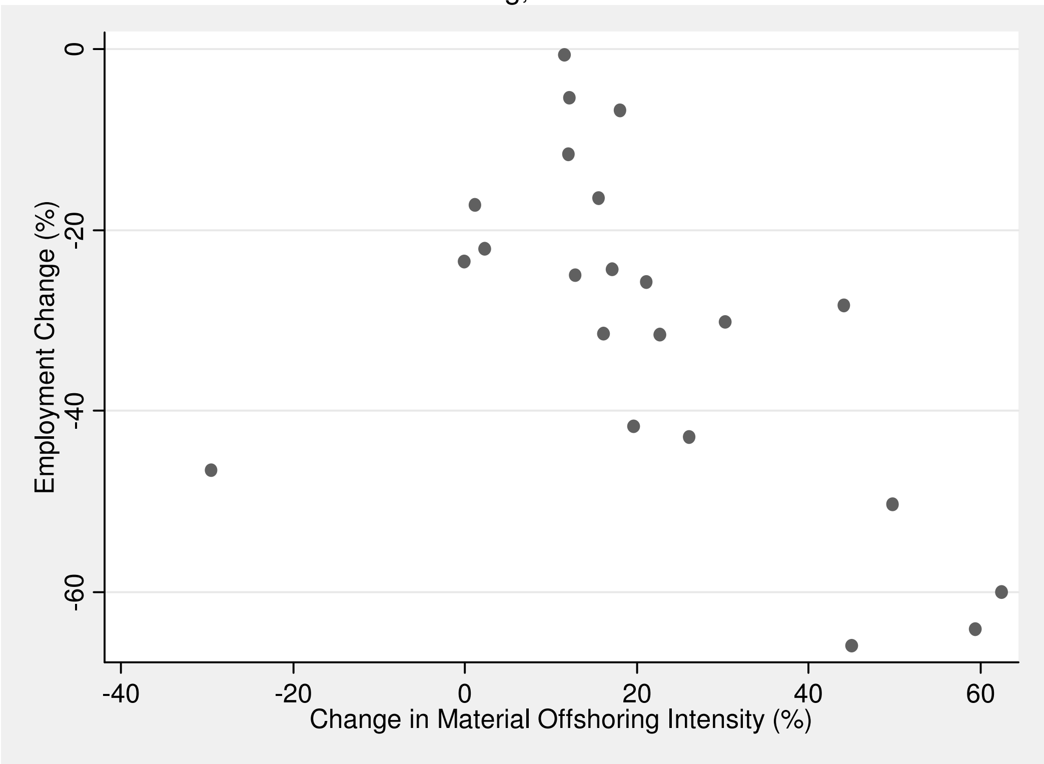
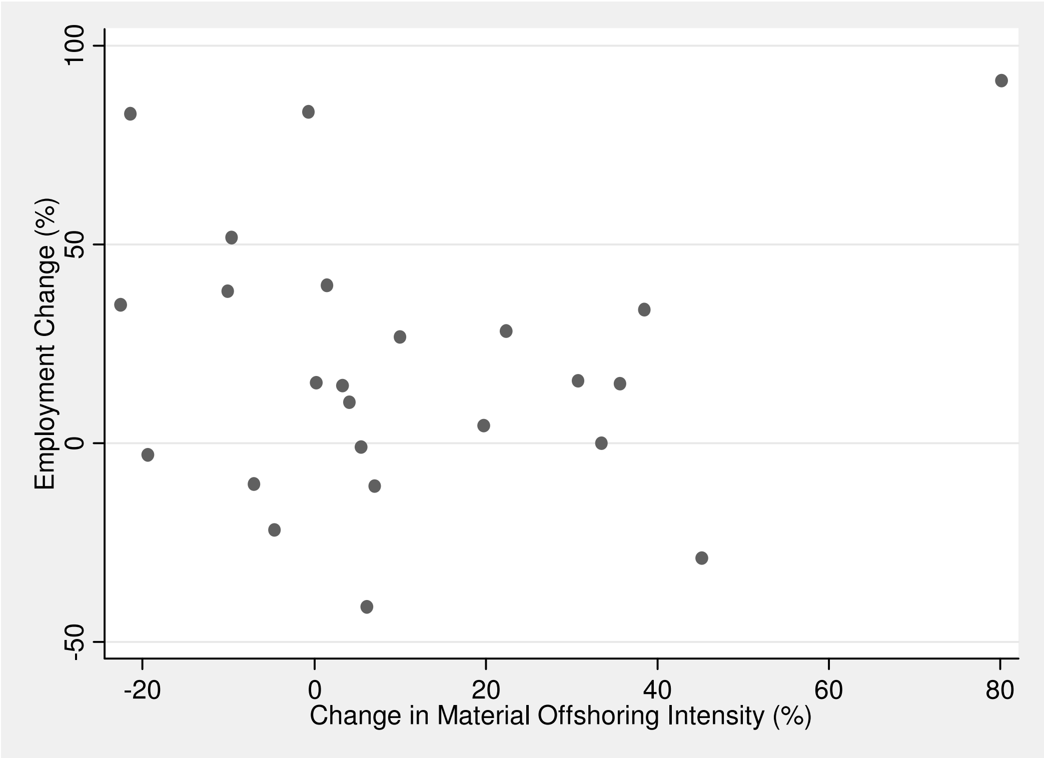


Figure II.14: Change in employment vs. change in material offshoring, German services, 1991 to 2000



II.5.4 Estimating Labor Demand Equations

We now estimate the effect of offshoring on employment using two common empirical specification of labor demand (Hamermesh, 1993)[85], namely log-linear conditional and unconditional labor-demand models. In the present context similar models have been estimated in modified form by Amiti and Wei (2005a, 2005b)[86] for the United States and the United Kingdom.

Empirical Specification

In the conditional model, the profit-maximizing level of labor demand N is determined by minimizing the costs of production subject to a constrained level of output Y and given exogenous factor prices ω. By Shepherd's lemma, labor demand can be derived as the partial derivative of the cost function $C(\omega,y)$ with respect to wages. Conditional labor demand in industry i at time t is then written as

$$\ln N_{it} = \alpha_0 + \alpha_1 \ln w_{it} + \alpha_2 \ln Y_{it} + \alpha_3 z_{it} \qquad \text{(II.1)}$$

where w is the wage rate and the core model has been augmented by a set of demand shift terms, z, that include measures of offshoring discussed above. Notice that in the conditional labor demand model the output level is exogenously given.

In contrast, in the unconditional labor-demand model output is endogenous. Firms maximize their profits by choosing both the optimal quantity of inputs and the level of output given exogenous input and output prices. Firms will then hire employees until the marginal value product of labor equals the wage rate. The unconditional labor demand can be represented as follows:

$$\ln N_{it} = \alpha_0 + \alpha_1 \ln w_{it} + \alpha_2 \ln p_{it} + \alpha_3 z_{it} \qquad \text{(II.2)}$$

with p denoting the price of output.

In order to account for potential time-invariant industry specific effects we take first differences of equations (II.1) and (II.2).[87] In addition, year dummies (D_t) are included to control for

[85] Hamermesh, D.S. (1993), "Labor Demand", Princeton University Press, Princeton, New Jersey.
[86] Amiti, M., and Wei, S.J. (2005a), "Fear of service outsourcing: is it justified?" *Economic Policy*, 20(42), 308-347.
Amiti, M. and Wei, S.J. (2005b), "Service Offshoring, Productivity, and Employment: Evidence from the United States," *IMF Working Papers* 05/238, International Monetary Fund.
[87] As a robustness check we also have estimated the regression equation in levels (but with sector specific fixed effects). The results are reported in Appendix A.2 and are broadly consistent with the results derived from the specification in time differences. However, one notable difference exists: while wide offshoring

unobserved time effects that are common across all industries. Assuming that input prices other than wages, such as the rental rate of capital, are a function of time and identical across industries, time dummies also account for changes in these other input prices (Amiti and Wei, 2005a).

Furthermore, the ratio of ICT investment to total gross output (ICT/Y) is included as a measure of technological progress (see Section I.5 for a detailed discussion of alternative indicators). Not accounting for technology in the estimation equation could result in a missing variable bias. In fact, both the offshoring and the technology variable are upward-trending. Therefore offshoring might spuriously pick up the effect of technological progress on employment if the latter is not explicitly modeled in the estimation equation. Finally, we include lags of the independent variables to allow for the fact that employment effects may not be instantaneous. Consequently, the two estimation equations read

$$\Delta \ln N_{it} = \alpha_0 + \alpha_1 \Delta \ln w_{it} + \alpha_2 \Delta \ln w_{i,t-1} + \alpha_3 \Delta \ln Y_{it} + \alpha_4 \Delta \ln Y_{i,t-1} + \alpha_5 \Delta z_{it} + \alpha_6 \Delta z_{i,t-1} + \alpha_7 \Delta (ICT/Y)_{it} + \alpha_8 \Delta (ICT/Y)_{i,t-1} + \alpha_9 D_t + \varepsilon_{it}, \tag{II.3}$$

$$\Delta \ln N_{it} = \alpha_0 + \alpha_1 \Delta \ln w_{it} + \alpha_2 \Delta \ln w_{i,t-1} + \alpha_3 \Delta \ln p_{it} + \alpha_4 \Delta \ln p_{i,t-1} + \alpha_5 \Delta z_{it} + \alpha_6 \Delta z_{i,t-1} + \alpha_7 \Delta (ICT/Y)_{it} + \alpha_8 \Delta (ICT/Y)_{i,t-1} + \alpha_8 D_t + \varepsilon_{it}. \tag{II.4}$$

The regressions are performed separately for the manufacturing and the service sector.[88] As a robustness check we also re-estimate the equations using two period differences. Estimates based on longer differences are in general less sensitive to biases arising from measurement error (Griliches and Hausman, 1986)[89]. They also account for lags in the adjustment of labor demand to shocks.[90]

Data

Sectoral employment data come from the EU KLEMS data set while offshoring measures are calculated from input-output data provided by the German Federal Statistical Office. The wage rate of an industry is computed as the ratio of total employee compensation divided by the number of employees. Gross output is measured at constant 1995 prices and the price index of

has no statistically significant effect on service sector employment when estimating the regression equation in first differences, we find some evidence for a negative effect in the level specification.

[88] By estimating separate regressions we allow all coefficients to differ between sectors. Given our focus on offshoring one may also pool the data and add interaction terms between offshoring and sectors dummies.

[89] Griliches, Z. and Hausman, J. (1986), "Errors in Variables in Panel Data," *Journal of Econometrics*, 31(1), 93-118.

[90] However, with overlapping data induced dependence of the error terms must result and therefore standard errors will be biased.

gross output is taken as a measure of *p*. All these variables as well as the ratio of ICT investment to total gross output are taken from the EU KLEMS data base and, hence, are not only available for Germany but potentially for other European countries as well. The data refers to industries at the (NACE) two-digit level. Notice, however, that for a number of industries data on ICT investment is only available at a (slightly) more aggregated level. For instance, for sectors 15 and 16 only data on the combined ICT investment of the two sectors is available; ICT investment (relative to gross output) is then assumed to be identical in these two sectors.[91]

Econometric Problems

While labor demand equations of the type presented in equations II.3 and II.4 are widely used in the literature, several issues regarding the validity of the estimation framework arise. Clearly, it is important to keep the limitations in mind when interpreting the regression results presented in the following.

Labor demand equations are likely to suffer from endogeneity biases and correlation between the error term and the right-hand side variables. First of all, there are good reasons to expect the wage rate to be endogenous. In general, both labor demand and supply depend on the wage level. Consequently, shocks to the labor demand will also affect wages. The disturbance term of the estimation equation will then be correlated with the wage rate.

On the other hand, wages can correctly be treated as exogenous when labor supply is perfectly elastic. In that case, wages depend solely on labor supply but are not affected by shocks to labor demand. Changes in the labor supply schedule, as measured by movements in wages, then trace out the labor demand curve. A perfectly elastic labor supply curve is a reasonable approximation to reality for small firms that arguably chose employment taking wages as exogenously given. It may also be a suitable assumption for sufficiently small subsectors of the economy but certainly not for the economy as a whole. Hence, as noted by Hamermesh (1993), the validity of this identifying assumption rests crucially on the level of aggregation of the data. The present study utilizes industry-level data at the two-digit level and hence endogeneity of the wage rate is a potential problem.

In principle, one could resort to an instrumental variable approach in order to tackle the endogeneity problem. However, finding a good instrument for identifying labor demand is very difficult and thus many labor demand studies refrain from doing so. Sometimes lagged wages are used as regressors even though “it is not entirely clear how this solves the problem” (Slaughter, 2002, p. 38)[92]. In any case, using lagged wages is not a suitable approach in the present context.

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[91] Similar problems exist with respect to the manufacturing sectors 17-19, 21-22, 27-28, 30-33, 34-35, 36-37 and the service sectors 60-63 and 71-74.

[92] Slaughter, M. J. (2001), "International Trade and Labor-Demand Elasticities," *Journal of International Economics*, 54(1), 27-56.

The (main) estimation equations are specified in time differences rather than in levels. Since differences of logs are approximately growth rates, one essentially would have to instrument the current growth rate of wages by its lagged value. However, the two are only very weakly correlated and hence the lagged growth rate of the wage rate is unlikely to be a valid instrument.

Not only wages but also output may be an endogenous variable in the conditional labor demand equation, as firms typically make their output and factor demand decisions jointly. As with wages, suitable instruments prove to be difficult to find. Lagged values are again not an option in the present context, since current and lagged output growth rates are only weakly correlated.

Another potential problem of the empirical approach described in the previous section is that it may fail to adequately address issues related to the stationarity of variables. By now, it is well known that a statistically significant correlation between non-stationary time series does not necessarily imply a meaningful relation. This is known as the spurious correlation problem and was first highlighted by Yule (1926)[93] and later discussed by Granger and Newbold (1974).[94] The problem should be of minor importance in the present context as the regression is specified in time differences. Hence, even if the variables of interest are integrated (of order one), the transformed series will be stationary. Nevertheless, the transformation implies a loss of information and, hence, a cointegration analysis (cf. Engle and Granger, 1987[95]) could offer additional insights.

Results

The results of estimating the specification in first differences for the manufacturing sector are shown in Table II.9. Columns (1) to (6) provide the estimation results for the conditional labor demand model while the findings of the unconditional model are given in columns (7) to (12). The models are separately estimated with the different types of offshoring indicators and with and without time dummies.

Inspecting the regression results shows that gross output, output prices and the wage rate enter the equation with the expected signs, even though the wage estimate sometimes turns statistically insignificant. ICT investment, though mostly negative in sign, does not exhibit a statistically significant effect on employment in manufacturing. Turning to the offshoring indicators, our main variables of interest, the coefficient estimates consistently exhibit a negative sign. The conditional labor demand estimates indicate that there is a statistically significant

[93] Yule, U. (1926), "Why Do We Sometimes get Nonsense-Correlations between Time Series? A Study in Sampling and the Nature of Time Series," *Journal of the Royal Statistical Society,* 89, 1-63.
[94] Granger, C.W.J., and Newbold, P. (1974), "Spurious Regressions in Econometrics," *Journal of Econometrics,* 2, 111-120.
[95] Engle, R.F., and Granger, C.W.J. (1987) "Co-Integration and Error Correction: Representation, Estimation and Testing". *Econometrica,* 55, 251–276.

negative correlation between employment and the lag of both the wide and the narrow offshoring measure once time dummies are included. In the unconditional labor demand model only the wide indicator remains statistically significant. Coefficient estimates of material and service offshoring are generally statistically insignificant.

The results change somewhat when two year differences are used instead (see Table II.10). Again, we find some evidence for a statistically significant negative effect of narrow and wide offshoring on employment. However, coefficient estimates are now larger. Estimating the conditional labor demand model with time dummies suggests that an increase in narrow outsourcing by 0.01 (or one percentage point) decreases labor demand by 0.81 per cent. While the effect of wide offshoring is not statistically significant in the conditional labor demand specification, the unconditional model with time dummies indicate that an increase in wide offshoring of 0.01 decreases labor demand by 0.70 per cent. Moreover, when using two period differences the measure of material offshoring is now found to be statistically significant and negatively correlated with labor demand in manufacturing.

Estimating the labor demand equation for the service sector produces results that are very different from those derived for manufacturing. We now find strong evidence for a positive effect of ICT investment (relative to gross output) on service sector employment. Both the current and the lagged value of the technology variable are positive in sign. The coefficient estimates of non-lagged ICT investment are generally larger than those of the lagged term and always statistically significant at any conventional level. Depending on the exact specification the estimation results suggest that an increase in (current) ICT investment by one percentage point is associated with an increase in employment of between 1.67 and 2.46 per cent.[96]

Turning to the offshoring indicators, coefficient estimates are for the most part positive which is in line with the descriptive evidence presented in the previous subsection. Estimating the model in first differences provides strong evidence for a (statistically significant) positive effect of narrow offshoring on employment. Both the current offshoring value and the first lag enter with a positive sign and are highly statistically significant (see columns (2) and (8) of Table II.11). We also find some evidence for a statistically significant positive effect of material offshoring on labor demand. The other two offshoring indicators are primarily negative in sign but never statistically significant. Using two rather than one period differences does also lend some evidence to a positive effect of narrow and material offshoring on labor demand in the service sector. However, only the coefficient on current narrow offshoring remains statistically significant (at the 5%level) while the lagged term is now rendered insignificant.

[96] When interpreting the magnitude of these coefficients it is important to note that the ratio of ICT investment to gross output is relatively small. Over the sample period the mean of the technology variable was .022 in the service and .007 in the manufacturing sector. Hence, an increase by just one percentage point (i.e. by .01) is a very large increase in relative terms.

Table II.9: Labor demand regression: One-year differences, manufacturing sector

	Conditional						Unconditional					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\Delta \ln Y_{it}$	.267***	.220***	.258***	.218***	.272***	.229***						
	(.058)	(.059)	(.054)	(.059)	(.057)	(.056)						
$\Delta \ln Y_{i,t-1}$	.203***	.151**	.201***	.132**	.205***	.146**						
	(.056)	(.060)	(.056)	(.060)	(.058)	(.063)						
$\Delta \ln p_{it}$							.380*	.301	.418**	.417***	.382*	.294
							(.194)	(.207)	(.167)	(.152)	(.195)	(.216)
$\Delta \ln p_{i,t-1}$							.134	.101	.163	.115	.125	.084
							(.120)	(.106)	(.120)	(.096)	(.122)	(.109)
$\Delta \ln w_{it}$	.020	.157	-.009	.174	-.027	-.107	-.244	-.016	-.262*	-.008	-.263	-.035
	(.248)	(.259)	(.252)	(.265)	(.250)	(.254)	(.158)	(.160)	(.151)	(.151)	(.170)	(.166)
$\Delta \ln w_{i,t-1}$	-.222**	-.0002	-.225**	-.003	-.230**	-.008	-.385***	-.080	-.401***	-.033	-.387***	-.074
	(.106)	(.116)	(.106)	(.122)	(.101)	(.120)	(.093)	(.107)	(.090)	(.101)	(.087)	(.111)
$\Delta (I_{ICT}/Y)_{it}$	-.120	-3.20	-.312	-2.55	.498	-1.38	.713	-3.96	.792	-4.96	.827	-2.98
	(5.98)	(5.72)	(6.02)	(5.66)	(6.03)	(5.96)	(5.36)	(6.03)	(5.55)	(6.22)	(5.70)	(6.12)
$\Delta (I_{ICT}/Y)_{I,t-1}$	2.00	-4.12	2.23	-5.53	2.99	-3.87	.221	6.03	.651	-7.50	.778	-5.49
	(4.92)	(5.86)	(4.81)	(5.70)	(5.32)	(5.93)	(5.43)	(6.85)	(5.49)	(6.49)	(5.91)	(6.93)
Δosn_{it}	-.114	-.217					-.073	-.237				
	(.186)	(.215)					(.228)	(.245)				
$\Delta osn_{i,t-1}$	-.232	-.320*					-.098	-.234				
	(.176)	(.189)					(.213)	(.207)				
Δosw_{it}			.128	-.083					-.014	-.343		
			(.202)	(.216)					(.245)	(.240)		
$\Delta osw_{i,t-1}$			-.225	-.453**					-.358	-.638***		
			(.180)	(.193)					(.223)	(.230)		
Δoss_{it}					-1.52	-2.40					-.348	-1.66
					(2.71)	(2.80)					(2.17)	(2.26)
$\Delta oss_{i,t-1}$					-1.96	-2.38					-.846	-1.23
					(2.07)	(2.61)					(1.92)	(2.14)
Δosm_{it}					-.038	-.182					-.032	-.228
					(.205)	(.237)					(.244)	(.250)
$\Delta osm_{i,t-1}$					-.032	-.157					-.035	-.199
					(.188)	(.202)					(.228)	(.223)
Year Dummies	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
R^2	.318	.384	.319	.394	.323	.397	.247	.346	.263	.403	.247	.355
N	176	176	176	176	176	176	176	176	176	176	176	176

***, **, *: statistically significant at 1, 5, and 10 % level, respectively; robust standard errors in parentheses

Table II.10: Labor demand regression: Two-year differences, manufacturing sector

	Conditional						Unconditional					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\Delta \ln Y_{it}$	.266***	.234***	.260***	.238***	.277***	.240***						
	(.065)	(.064)	(.065)	(.063)	(.063)	(.060)						
$\Delta \ln Y_{i,t-1}$	.270***	.228***	.259***	.179**	.273***	.233***						
	(.072)	(.078)	(.070)	(.079)	(.069)	(.070)						
$\Delta \ln p_{it}$							.569***	.507**	.682***	.714***	.562***	.491**
							(.197)	(.223)	(.208)	(.195)	(.194)	(.221)
$\Delta \ln p_{i,t-1}$							.127	.057	.093	-.055	.091	-.009
							(.190)	(.172)	(.197)	(.156)	(.193)	(.171)
$\Delta \ln w_{it}$	-.012	.033	-.041	-.004	-.072	-.059	-.154	-.085	-.182	-.111	-.2000	-.161
	(.248)	(.249)	(.281)	(.270)	(.221)	(.205)	(.228)	(.224)	(.229)	(.223)	(.223)	(.203)
$\Delta \ln w_{i,t-1}$	-.272	.069	-.309	.098	-.305*	-.076	-.569***	-.128	-.595***	.005	-.575***	-.062
	(.190)	(.280)	(.208)	(.291)	(.180)	(.248)	(.154)	(.167)	(.158)	(.174)	(.152)	(.173)
$\Delta (I_{ICT}/Y)_{it}$	-5.43	-6.85	-4.87	-5.37	-3.63	-3.89	-5.37	-7.89	-6.14	-10.2	-5.26	-7.16
	(6.70)	(6.25)	(6.92)	(6.66)	(6.85)	(6.70)	(7.09)	(7.70)	(7.18)	(7.74)	(7.51)	(7.91)
$\Delta (I_{ICT}/Y)_{I,t-1}$	2.54	-2.87	1.33	-6.65	2.87	-3.20	2.83	-2.65	3.36	-3.25	3.84	-1.50
	(6.53)	(5.90)	(6.82)	(6.86)	(7.24)	(6.44)	(7.32)	(8.13)	(7.54)	(7.52)	(8.12)	(8.42)
$\Delta\, osn_{it}$	-.773***	-.807***					-.503	-.579				
	(.242)	(.255)					(.367)	(.361)				
$\Delta\, osn_{i,t-1}$	.116	-.051					.138	-.060				
	(.250)	(.267)					(.418)	(.403)				
$\Delta\, osw_{it}$			-.258	-.364					-.426	-.696**		
			(.309)	(.306)					(.353)	(.321)		
$\Delta\, osw_{i,t-1}$			.045	-.338					.000	-.363		
			(.255)	(.271)					(.374)	(.353)		
$\Delta\, oss_{it}$					-1.44	-2.24					.804	-.279
					(3.53)	(3.74)					(2.84)	(3.06)
$\Delta\, oss_{i,t-1}$					-3.30	-3.53					-2.23	-2.89
					(3.30)	(3.64)					(2.59)	(3.01)
$\Delta\, osm_{it}$					-.833***	-.86***					-.591*	-.698**
					(.247)	(.26)					(.353)	(.334)
$\Delta\, osm_{i,t-1}$					.407	.20					.181	.028
					(.311)	(.31)					(.439)	(.416)
Year Dummies	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
R^2	.423	.481	.382	.455	.453	.52	.321	.405	.324	.454	.329	.429
N	154	154	154	154	154	154	154	154	154	154	154	154

Table II.11: Labor demand regression: One-year differences, service sector

	Conditional						Unconditional					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\Delta \ln Y_{it}$	.006	.005	-.008	-.019	.012	-.022						
	(.081)	(.080)	(.097)	(.086)	(.087)	(.086)						
$\Delta \ln Y_{i,t-1}$	.114	.118	.109	.117	.121	.132						
	(.088)	(.089)	(.091)	(.094)	(.096)	(.102)						
$\Delta \ln p_{it}$							-.069	-.092	-.055	-.067	-.071	-.093
							(.120)	(.130)	(.123)	(.136)	(.126)	(.136)
$\Delta \ln p_{i,t-1}$							.374***	.360***	.361***	.362***	.380***	.371***
							(.111)	(.117)	(.113)	(.120)	(.114)	(.120)
$\Delta \ln w_{it}$	-.146	-.269**	-.086	-.182	-.094	-.206*	-.224**	-.307***	-.165*	-.224**	-.166*	-.241**
	(.090)	(.103)	(.096)	(.117)	(.097)	(.122)	(.093)	(.099)	(.092)	(.101)	(.091)	(.101)
$\Delta \ln w_{i,t-1}$	-.201**	-.411***	-.188**	-.352***	-.177**	-.366***	-.256***	-.414***	-.242***	-.357***	-.231***	-.376***
	(.085)	(.098)	(.086)	(.103)	(.086)	(.103)	(.081)	(.096)	(.083)	(.101)	(.085)	(.103)
$\Delta (I_{ICT}/Y)_{it}$	1.67***	1.70***	2.12***	2.14***	2.11***	2.08***	1.89***	2.09***	2.29***	2.46***	2.27***	2.40***
	(.613)	(.592)	(.612)	(.604)	(.615)	(.614)	(.631)	(.666)	(.649)	(.683)	(.649)	(.693)
$\Delta (I_{ICT}/Y)_{I,t-1}$	2.24***	2.13***	1.96***	1.82**	1.91***	1.87**	2.14***	1.60**	1.88**	1.31*	1.85**	1.43*
	(.680)	(.725)	(.671)	(.770)	(.668)	(.777)	(.745)	(.763)	(.747)	(.791)	(.748)	(.814)
$\Delta\ osn_{it}$	.374*	.507**					.377*	.492**				
	(.224)	(.218)					(.211)	(.215)				
$\Delta\ osn_{i,t-1}$	.611***	.779***					.627***	.764***				
	(.201)	(.214)					(.232)	(.242)				
$\Delta\ osw_{it}$			-.049	-.019					-.065	-.046		
			(.146)	(.142)					(.117)	(.111)		
$\Delta\ osw_{i,t-1}$			.031	.064					.002	.069		
			(.107)	(.124)					(.102)	(.114)		
$\Delta\ oss_{it}$					-.052	-.040					-.111	-.093
					(.158)	(.150)					(.120)	(.110)
$\Delta\ oss_{i,t-1}$					-.067	.028					-.015	.056
					(.108)	(.120)					(.102)	(.114)
$\Delta\ osm_{it}$					.020	.246					.287	.418
					(.339)	(.315)					(.289)	(.266)
$\Delta\ osm_{i,t-1}$					.398	.679					.235	.428
					(.385)	(.413)					(.322)	(.325)
Year Dummies	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
R^2	.317	.369	.292	.329	.296	.339	.352	.396	.327	.359	.333	.368
N	192	192	192	192	192	192	192	192	192	192	192	192

***, **, *: statistically significant at 1, 5, and 10 % level, respectively; robust standard errors in parentheses

Table II.12: Labor demand regression: Two-year differences, service sector

	Conditional						Unconditional					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\Delta \ln Y_{it}$	-.086	-.071	-.117	-.126	-.124	-.130						
	(.131)	(.130)	(.140)	(.142)	(.141)	(.143)						
$\Delta \ln Y_{i,t-1}$	.251*	.247*	.263*	.277*	.280*	.315**						
	(.141)	(.139)	(.149)	(.149)	(.154)	(.152)						
$\Delta \ln p_{it}$							-.202	-.246	-.157	-.186	-.184	-.231
							(.154)	(.167)	(.164)	(.175)	(.165)	(.174)
$\Delta \ln p_{i,t-1}$							.495***	.487***	.451***	.460**	.490***	.479***
							(.157)	(.172)	(.168)	(.181)	(.170)	(.181)
$\Delta \ln w_{it}$	-.279*	-.338**	-.093	-.135	-.110	-.176	-.280**	-.309**	-.109	-.115	-.144	-.152
	(.155)	(.166)	(.180)	(.209)	(.181)	(.212)	(.133)	(.146)	(.143)	(.171)	(.144)	(.173)
$\Delta \ln w_{i,t-1}$	-.249*	-.520***	-.288**	-.510***	-.264**	-.560***	-.340***	-.535***	-.362***	-.511***	-.332**	-.543***
	(.142)	(.160)	(.150)	(.178)	(.152)	(.171)	(.129)	(.145)	(.135)	(.162)	(.136)	(.166)
$\Delta (I_{ICT}/Y)_{it}$	1.95***	2.22***	2.39***	2.64***	2.32***	2.44***	2.21***	2.74***	2.65***	3.12***	2.58***	2.93***
	(.658)	(.758)	(.752)	(.898)	(.740)	(.899)	(.714)	(.867)	(.799)	(.943)	(.807)	(.956)
Δ	2.02***	1.67*	1.86**	1.52	1.82**	1.65	1.89**	1.07	1.69*	.921	1.69*	1.15
$(I_{ICT}/Y)_{I,t-1}$	(.738)	(.892)	(.864)	(1.12)	(.855)	(1.16)	(.937)	(1.06)	(.984)	(1.14)	(.997)	(1.18)
$\Delta\, osn_{it}$	.781**	.897**					.803**	.958***				
	(.355)	(.342)					(.349)	(.356)				
$\Delta\, osn_{i,t-1}$	.338	.509					.343	.428				
	(.374)	(.377)					(.422)	(.452)				
$\Delta\, osw_{it}$			-.184	-.187					-.108	-.105		
			(.248)	(.260)					(.203)	(.204)		
$\Delta\, osw_{i,t-1}$			-.095	.025					-.127	-.064		
			(.207)	(.232)					(.154)	(.170)		
$\Delta\, oss_{it}$					-.179	-.199					-.181	-.172
					(.276)	(.285)					(.209)	(.211)
$\Delta\, oss_{i,t-1}$					-.148	-.040					-.108	-.053
					(.216)	(.234)					(.175)	(.187)
$\Delta\, osm_{it}$					.031	.224					.551	.635
					(.673)	(.637)					(.450)	(.408)
$\Delta\, osm_{i,t-1}$					.608	1.48**					.023	.594
					(.661)	(.708)					(.402)	(.439)
Year Dummies	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
R^2	.405	.455	.383	.413	.387	.432	.424	.465	.397	.421	.404	.433
N	168	168	168	168	168	168	168	168	168	168	168	168

***, **, *: statistically significant at 1, 5, and 10 % level, respectively; robust standard errors in parentheses

II.6 Summary

Part II of the study has provided an in-depth analysis of offshoring and its effect on employment. We first defined offshoring as either the transfer of the production of goods and services to a foreign affiliate (offshore in-house sourcing) or as the contracting-out of production activities to a foreign non-affiliated supplier (offshore outsourcing). It was then shown that – from a theoretical point of view – it is not clear whether the overall employment effect of offshoring is positive or negative. While in the short-run offshoring is likely to displace domestic jobs, it may also boost employment by enhancing firm productivity and strengthen competiveness. Additionally, at the aggregate level offshoring can increase foreign income and demand for exports to those markets.

Next, we turned to the measurement of offshoring. Arguably the most promising measure in the context of our study is the fraction of imported intermediates in total inputs. This indicator can readily be constructed from input-output tables. Data are sufficiently comparable across countries, since harmonized input-output tables are provided by the OECD.

Finally, using data from Germany a case study on the development of offshoring in the 1990s and its subsequent effect on the labor market was performed. Offshoring is generally found to be on the rise in the 1990s. Nevertheless, there are pronounced differences in the evolution of this phenomenon across sectors. While still more important in German manufacturing, in the 1990s offshoring is associated with the sectoral extent of the ICT revolution. Finally, in order to assess the effect on employment labor demand equations were estimated separately for the manufacturing and the service sector with an explicit role for offshoring. We find evidence for the hypothesis that offshoring has a negative effect on employment in the manufacturing sector while for the service sector the correlation emerges as positive.

Interestingly, this result is broadly consistent with evidence presented recently by Bachmann and Braun (2008)[97]. Combining individual- with industry-level data, the study analyses the effect of offshoring on labor market dynamics in Germany. Offshoring is found to have no or a slightly negative impact on job stability in the manufacturing sector, but it is associated with increased job stability in the service sector. The authors argue that differences in the economic situation of the two sectors may account for the contrasting findings. Firms in the manufacturing sector may have primarily relocated *existing* production processes to foreign production sites in an attempt to stay internationally competitive. Since this involves the displacement of existing domestic jobs, the negative, direct effect of offshoring may have been predominant in manufacturing. The German service sector, on the other hand, was constantly expanding in the 1990s. Hence, the rapid growth of offshoring in the service sector may have been driven by domestic firms contracting out *newly created* production processes to foreign (affiliated or non-affiliated) firms.

[97] Bachmann, R. and Braun, S. (2008), "The Impact of International Outsourcing on Labour Market Dynamics in Germany," *SFB 649 Discussion Paper* 2008-020.

As offshoring should also have boosted firm productivity, domestic workers may then have reaped the benefits of offshoring while their jobs were not directly put at risk.

A2. Appendix Part II: Additional Regression Results

Table II.13: Fixed effect labor demand regression: Manufacturing sector, specification in levels

	Conditional						Unconditional					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ln Y_{it}	.125	.116	.125	.110	.197**	.192*						
	(.095)	(.108)	(.095)	(.109)	(.084)	(.102)						
ln $Y_{i,t-1}$	.339***	.355***	.319***	.286***	.351***	.345***						
	(.075)	(.096)	(.072)	(.094)	(.066)	(.083)						
ln p_{it}							.321	.264	.531**	.520**	.313	.234
							(.216)	(.253)	(.220)	(.229)	(.220)	(.255)
ln $p_{i,t-1}$							.233	.251	.112	.004	.134	.118
							(.242)	(.258)	(.243)	(.244)	(.239)	(.254)
ln w_{it}	-.049	-.014	.035	.072	-.164	-.147	-.047	-.032	-.047	-.033	-.056	-.072
	(.268)	(.270)	(.319)	(.288)	(.227)	(.213)	(.247)	(.253)	(.263)	(.244)	(.261)	(.245)
ln $w_{i,t-1}$	-.593***	-.360	-.637***	-.243	-.568***	-.363	-.721***	-.639***	-.676***	-.323	-.701***	-.572**
	(.196)	(.220)	(.218)	(.229)	(.171)	(.232)	(.186)	(.222)	(.191)	(.243)	(.187)	(.240)
$(I_{ICT}/Y)_{it}$	-9.75	-7.37	-11.5	-6.38	-6.21	-3.01	-1.69	.171	-4.24	-2.39	-.931	.553
	(7.00)	(7.68)	(7.15)	(7.54)	(6.54)	(6.92)	(7.14)	(8.28)	(7.04)	(8.13)	(7.29)	(8.06)
$(I_{ICT}/Y)_{I,t-1}$	2.82	1.99	5.71	-3.75	3.11	-1.14	2.02	-6.52	6.27	-6.91	5.09	-4.88
	(8.25)	(9.81)	(9.00)	(10.1)	(7.90)	(8.65)	(8.23)	(11.2)	(8.44)	(10.5)	(8.73)	(10.9)
osn_{it}	-.753**	-.804**					-.430	-.395				
	(.317)	(.351)					(.486)	(.526)				
$osn_{i,t-1}$	-.478	-.478					-.512	-.643				
	(.392)	(.420)					(.561)	(.593)				
osw_{it}			-.409	-.569					-.340	-.618		
			(.337)	(.360)					(.381)	(.421)		
$osw_{i,t-1}$			-.692**	-.873***					-.730*	-.947**		
			(.320)	(.329)					(.434)	(.427)		
oss_{it}					-2.18	-1.70					-.822	-.603
					(3.60)	(3.97)					(3.54)	(3.93)
$oss_{i,t-1}$					-4.56	-5.20					-1.08	-2.10
					(3.32)	(3.74)					(3.31)	(3.59)
osm_{it}					-.790***	-.759**					-.500	-.475
					(.284)	(.322)					(.430)	(.474)
$osm_{i,t-1}$					-.136	-.233					-.541	-.738
					(.316)	(.333)					(.496)	(.514)
Year Dummies	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
R^2 (within)	.783	.789	.777	.797	.825	.831	.725	.734	.740	.771	.736	.752
N	198	198	198	198	198	198	198	198	198	198	198	198

***, **, *: statistically significant at 1, 5, and 10 % level, respectively; robust standard errors in parentheses

Table II.14: Fixed effect labor demand regression: Service sector, specification in levels

	Conditional						Unconditional					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ln Y_{it}	-.221	-.159	.114	-.084	-.180	-.137						
	(.158)	(.165)	(.152)	(.156)	(.157)	(.154)						
ln $Y_{i,t-1}$	.517***	.411**	.436**	.358**	.514***	.417**						
	(.181)	(.170)	(.176)	(.172)	(.181)	(.172)						
ln p_{it}							-.472**	-.514**	-.481**	-.528**	-.535***	-.584**
							(.198)	(.250)	(.208)	(.261)	(.202)	(.240)
ln $p_{i,t-1}$							.742***	.610**	.716***	.624***	.817***	.681***
							(.227)	(.277)	(.217)	(.262)	(.221)	(.248)
ln w_{it}	-.588***	-.359*	-.316	-.136	-.405	-.263	-.435**	-.235	-.230	-.046	-.382*	-.192
	(.222)	(.193)	(.256)	(.226)	(.254)	(.218)	(.211)	(.200)	(.207)	(.196)	(.200)	(.190)
ln $w_{i,t-1}$	-.037	-.823***	-.081	-.737***	-.001	-.755***	-.067	-.821***	-.071	-.750***	-.007	-.804***
	(.175)	(.195)	(.184)	(.226)	(.183)	(.220)	(.175)	(.208)	(.165)	(.218)	(.158)	(.213)
$(I_{ICT}/Y)_{it}$	3.39***	3.83***	4.22***	4.69***	3.99***	4.27***	4.61***	4.98***	5.44**	5.80***	4.96***	5.16***
	(.981)	(1.06)	(1.24)	(1.31)	(1.19)	(1.25)	(1.14)	(1.37)	(1.21)	(1.49)	(1.23)	(1.45)
$(I_{ICT}/Y)_{I,t-1}$	1.21	.008	.860	-.279	.932	-.076	-.027	-1.33	-.410	-1.66	-.085	-1.10
	(1.15)	(1.28)	(1.47)	(1.48)	(1.41)	(1.43)	(1.48)	(1.73)	(1.49)	(1.68)	(1.51)	(1.62)
osn_{it}	1.21***	1.08**					.978*	1.07*				
	(.430)	(.464)					(.496)	(.550)				
$osn_{i,t-1}$	.229	.530					.286	-.384				
	(.463)	(.521)					(.587)	(.647)				
osw_{it}			.089	.105					-.043	.071		
			(.254)	(.269)					(.235)	(.246)		
$osw_{i,t-1}$			-.619***	-.455**					-.394**	-.303		
			(.185)	(.195)					(.182)	(.185)		
oss_{it}					.058	-.034					-.141	-.156
					(.288)	(.293)					(.234)	(.260)
$oss_{i,t-1}$					-.742***	-.528**					-.303	-.239
					(.216)	(.206)					(.192)	(.189)
osm_{it}					-.640	-.148					1.04**	1.03**
					(.712)	(.611)					(.452)	(.497)
$osm_{i,t-1}$					1.87*	3.04***					.981	2.18***
					(1.07)	(1.13)					(.743)	(.826)
Year Dummies	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
R^2(within)	.547	.609	.538	.578	.547	.605	.536	.600	.517	.568	.533	.596
N	216	216	216	216	216	216	216	216	216	216	216	216

***, **, *: statistically significant at 1, 5, and 10 % level, respectively; robust standard errors in parentheses

Part III: ICT, Skills and Jobs

III.1 The Influence of ICT on Skilled Workers – Skill-biased Technical Change

The previous two parts of this report have analyzed the effects of ICT on general levels of employment and the European labor market. This chapter is closely connected to them, but focuses additionally on distributional effects. While the first two chapters analyze the effect of ICT on total employment effects and its connection to new trends in offshoring, this chapter focuses on the skill-based characteristics of ICT innovations for employment. Thus it summarizes the ongoing discussion about the effects of ICT on *relative* employment and compensation of workers with different levels of skills. This chapter therefore provides a more nuanced view of how ICT affects separate groups within the European labor markets compared to the overall picture presented in part I of this report. This part presents an analysis of the different employment effects of ICT on high-, medium- and low-skilled workers. While in the first part different effects of ICT innovations on labor demand are found, this part is concerned with the individual reactions of employment and compensation shares of the skill groups which in the end are one source of the aggregate trends discussed in the first part.

Over the last decades shifts in the demand for workers with different skills became a common phenomenon and a highly discussed topic in economics. These shifts affect simultaneously relative employment and relative compensation of workers with different skills in many countries, especially in the US and the UK. Thus this chapter analyzes to which extent these demand changes have been driven by ICT. Some of the relevant issues have already been mentioned in previous chapters, but as there is a large body of literature concerned with this topic, this chapter will cover these issues in more detail. It will conclude with a suggested econometric specification for exploring the relationship between ICT investment and the structure of relative employment and wages.

Before the 1980s, income inequality was believed to be relatively stable. In the early 1990s economists uncovered that wage inequality in the Anglo-Saxon countries has increased since the 1970s (see, for instance, Levy and Murnane 1992[98], Katz and Murphy 1992[99], and Juhn, Murphy and Pierce 1993[100]). In the aftermath, many studies confirmed this observation and tried to find reasons for this sudden change in wage inequality. One attribute of this observed changed was an especially pronounced increase in the wage premium for educated or skilled workers. As the

[98] Levy, F. and Murnane, R.J. (1992), "US Earnings Levels and Earnings Inequality: A Review of Recent Trends and Proposed Explanations", *Journal of Economic Literature*, 30(3), 1333-1381.
[99] Katz, L.F. and Murphy, K.M. (1992), "Changes in Relative Wages, 1963-1987: Supply and Demand Factors", *Quarterly Journal of Economics*, 107(1), 35-78.
[100] Juhn, C., Murphy, K.M., and Pierce, B. (1993), "Wage Inequality and the Rise in Returns to Skill", *The Journal of Political Economy*, 101(3), 410-442.

supply of skilled workers rose, increasing relative wages for this group implied an even faster increasing demand for skilled workers. Thus researchers began searching for reasons for the striking increases in both the demand for skilled workers and wage inequality (Lemieux 2008).[101]

By the late 1970s, computers had begun to play an increasingly important role in all industries. It became conventional wisdom that technological change, characterized by the introduction of new ICTs, lay behind the rising demand for skilled workers. Researchers argued that skilled workers are either more qualified or more productive using computers at work than unskilled workers. As quality adjusted prices for ICT decreases, the demand for skilled workers increases due to this complementarity (Machin and Van Reenen 2007)[102]. Thus skill-biased technological change (SBTC) became the standard explanation for rising relative demand for skilled workers and thus for inequality in the US and the UK. This technical progress was also responsible for inducing changes in production techniques and other organizational developments (Katz and Autor 1999)[103].

Studies analyzing wage inequality in other OECD countries such as countries within continental Europe also find evidence for a rising inequality and demand of skilled workers. Nevertheless, these findings were less pronounced than for the US or the UK. Some researchers criticized the SBTC hypothesis and argued for alternative explanations to the rising inequality. One prominent explanation for the rise in inequality and the demand for skilled workers is the emergence of globalization and offshoring.[104]

Another alternative reason for the rising inequality is shifts in labor market institutions.[105] In brief, some researchers argue that declining minimum wages, shifts in bargaining power and changing collective bargaining structures have lowered wages and employment for low-skilled workers.[106] Machin and Van Reenen (2007) argue that institutional differences may explain the

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[101] Lemieux, T. (2008), "The Changing Nature of Wage Inequality", *Journal of Population Economics*, Springer, 21(1), 21-48.
[102] Machin, S. and Van Reenen, J. (2007), "Changes in Wage Inequality", *CEPR Discussion Paper,* Special Paper No. 18.
[103] Katz L.F. and Autor, D. (1999), "Changes in the Wage Structure and Earnings Inequality", in O. Ashenfelter and D. Card, eds., "*Handbook of Labor Economics vol. III",* Elsevier, Amsterdam.
[104] See Chapter II of this report for a thorough discussion of the effect of globalization and offshoring on European labor markets.
[105] See also the Section I.6 of this report for a brief discussion
[106] Katz and Autor (1999) discuss this strand of the literature in detail in Chapter 6 of their contribution to the Handbook of Labor Economics. Card and DiNardo (2002) argue in a prominent article against the role of SBTC. DiNardo et al. (1996) discuss a strong effect of real minimum wages on the rising wage inequality in the US next to the union and supply/demand effects. In a recent paper Lemieux (2008) reviews the evolution of the literature concerning wage inequality and also makes a strong case for institutions as the major cause for the observed increase in inequality.
Card, D. and DiNardo, J.E. (2002), "Skill-Biased Technological Change and Rising Wage Inequality: Some Problems and Puzzles", *Journal of Labor Economics*, 20(4), 733-783.
DiNardo, J., Fortin, N.M., and Lemieux, T. (1996), "Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach", *Econometrica*, 64(5), 1001-1044.

observed cross-country differences in the magnitude of inequality induced by SBTC.[107] While SBTC is a global trend, labor market institutions influence how strongly wages and employment react (see also Blaun and Kahn 1996[108]). A common argument is, for example, that while in the Anglo-Saxon countries wages of low- and medium-skilled worker decreased, unemployment rates of these groups increased in continental Europe instead.[109]

In the most recent period, it has become evident that inequality had not grown continuously between the 1980s and the 1990s, giving rise to new refinements to existing explanations of rising inequality. In the 1990s, inequality in the lower part of the wage distribution remained roughly constant in the US, while it continued to rise sharply at the top. One newer line of reasoning holds that the influence of SBTC on the wage distribution is not linear in skill levels, but rather depends on workers' specific tasks. This richer vision of the SBTC hypothesis is also complemented by the argument that labor market institutions also have a visible influence on the development of the wage distribution, especially at its lower end (Machin and Van Reenen 2007).

In Part III, we will shed some light on the influence of ICT on the development of the wage and employment distribution in the US and Europe. We begin with an overview of available data and the central literature, summarizing the central studies concerning SBTC and the evolution of the SBTC hypothesis. Third, an econometric model will be proposed, which can be used to analyze the effect of ICT on wages and employment of differently skilled workers in Europe. In a last step, an econometric specification is implemented using data from Germany with some promising results.

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[107] See also Freeman and Katz (1995).
Freeman, R. B, and Katz, L.F. (1995), "Differences and Changes in Wage Structures", University of Chicago Press, Chicago.

[108] Blau, F.D. and Kahn, L.M. (1996), "International Differences in Male Wage Inequality: Institutions versus Market Forces", *The Journal of Political Economy*, 105(4), 791-837.

[109] For a discussion of this argument see Card et al. (1999). They argue against this claim although they see a correlation between the wage development for skill groups and computer use. Nevertheless they find no consistent connection between the wage and employment evolutions for the US, Canada and France.
Card, D., Kramarz, F. and Lemieux, T. (1999), "Changes in the Relative Structure of Wages and Employment: A Comparison of the United States, Canada, and France", *The Canadian Journal of Economics*, 32(4), 843-877

III.2 Rising Inequality and Rising Skill Premium in Advanced Economies

III.2.1 United States

In their contribution to the AEA Papers and Proceedings in 1993, Murphy and Welch (1993)[110] highlighted rising inequality of labor compensation in the US. Using data from the CPS (Current Population Survey), they find that during the preceding two decades the wages above the median increased while the wages below the median decreased. Taking a closer look at this development the authors describe the movement of relative wages by skill. The skill premium of college educated workers compared to high school educated workers increased rapidly in the 1980s after a drop in the premium in the 1970s. These trends in relative wages can be seen in connection to the supply side of high-skilled labor. During these decades the supply of highly educated workers increased, primarily due to the baby boomer generation. This can explain the drop of the wage premium in the 1970s, but hints at a pronounced increase in the demand for high-skilled worker in the 1980s that has overcompensated the increasing skill supply. Rising wage dispersion within cohorts hints at an increase in the price for skill. Differences in wages within the same educational and experience group may indicate that workers with unobservable higher skills are paid more. Rising within-groups inequality may thus be a sign of rising skill prices.[111]

Although Murphy and Welch viewed the rise in inequality as a long-run phenomenon, the observed increase in the price for skill was most dramatic in the 1980s. Bound and Johnson (1992)[112] analyze US data from the 1970 and 1980s. They also find a decrease in the wage premium of college educated workers in the US during the 1970s and an increase in this premium in the 1980s. Between 1990 and 2005 the skill differential continued to increase, but at a slower pace. The medium- to low-skilled wage differential, virtually constant in previous decades, also began to increase starting in the 1980s. After 2000 this wage differential appears to have declined again (Goldin and Katz 2007)[113].

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[110] Murphy, K. M. and Welch, F. (1993), "Inequality and Relative Wages", *American Economic Review Papers and Proceedings*, 83(2), 104-109.

[111] The rising within-groups inequality (or residual wages) is found to be one of driving forces of wage inequality in the US (see, for instance, Juhn et al. 1993). Lemieux (2006) discusses this finding and argues for a much lower residual wage inequality than formerly assumed due to data inaccuracies and estimation methods.
Lemieux, T. (2006), "Increasing Residual Wage Inequality: Composition Effects, Noisy Data, or Rising Demand for Skill?", *American Economic Review*, 96(3), 461-498.

[112] Bound, J. and Johnson, G. (1992), "Changes in the Structure of Wages in the 1980's: An Evaluation of Alternative Explanations", *American Economic Review*, 82(3), 371-392.

[113] Goldin, C. and Katz, L. F. (2007), "The Race between Education and Technology: the Evolution of US Educational Wage Differentials, 1890 to 2005", in "*The Race between Education and Technology",* Harvard University Press, forthcoming 2008.

Using US census data Autor et al. (2007) find similar wage developments and stress that the skill premium for high-skilled workers with a post-graduate degree increased at a higher growth rate after 1990. The increasing general wage inequality is mostly due to increases in the upper tail of the wage distribution. Wage inequality in the lower part of the distribution increased only until the mid-1980s, and decreased afterwards. The authors find expanding employment shares in skill-intensive occupations and decreasing shares in low-skilled occupations until the 1990s. Since the 1990s the employment shares in occupations for high and less educated workers grew while for medium educated workers the employment shares contracted.

III.2.2 Europe

Taking the US discussion to an international level, Davis (1992)[114] explored wage movements and inequality in 13 industrialized countries. Similar to the developments in the US he found increasing wage inequality in Australia, Canada, West Germany and the UK in the 1980s. In contrast, Sweden exhibited only a small rise in inequality, while wage inequality remained almost constant in France and the Netherlands over the same period. In the countries considered in the study, real wages stayed constant or decreased slightly, with the exception of the UK. The rising inequality therefore implied a real wage decline for workers at the lower tail of the wage distribution.

Davis (1992) also isolated common patterns in the development of wage differentials across advanced countries. In the US, UK, Canada, Sweden, Australia, and West Germany the education wage differentials increased in the 1980s. In Japan, the education differentials remained constant and decreased in the Netherlands. Taking into account the decrease in education differentials in the 1970s in the US, the increase in the education wage premium in the 1980s only compensated for losses in the 1970s. The increase of the differentials in the US was more remarkable compared to the other advanced countries although the general trends are common.

The OECD Employment Outlook (1993)[115] examined increased wage dispersion in greater detail. The authors find increasing wage dispersion in a majority of OECD countries. The Nordic countries Denmark, Finland and Norway as well as Italy display constant dispersion, while in Germany dispersion decreased in the 1980s. The increased dispersion is primarily due to a wage increase in the upper tail of the wage distribution. Only in some cases wage losses in the lower tail were observable. In their discussion of potential reasons for increased wage dispersion in developed countries, the OECD focused on the evolution of the skill differential. Reviewing several articles which analyze educational differentials in different countries, the authors conclude that wage-skill differentials rose in most countries in the 1980s after a fall in the 1970s.

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[114] Davis, S. J. (1992), "Cross-Country Patterns of Change in Relative Wages", *NBER Working Paper* No. 4085.

[115] OECD (1993), "Earning inequality: Changes in the 1980s", *OECD Employment Outlook 1993*, Chapter 5, 158-184.

In fact, only Germany displayed a falling skilled wage differential in both decades. The increase was particularly strong in the UK and the US.

For Germany and the UK similar "polarizing" trends as in the US can be observed from the 1990s up to the early 2000s. Dustmann et al. (2007)[116] contrasted wage developments in Germany with those in the US. Inequality in the lower tail of the wage distribution hardly increased in the 1980s, while it rose markedly during the 1990s. During both decades the upper tail wage inequality was rising.[117] These developments are labeled "polarization" as middle income workers lose relative to less and high educated workers. Evidence for rising polarization of employment in the UK is given by Goos and Manning (2007)[118]. In Section 4 we will present further supporting evidence on the employment and compensation shares of separate skill groups for selected European countries.

[116] Dustmann, C., Ludsteck, J. and Schönerg, U. (2007), "Revisiting the German Wage Structure", *IZA Discussion Paper Series*, No. 2685.

[117] Gernandt and Pfeiffer (2007) confirm the result of growing inequality in Germany since 1992/93 using a different dataset, the German Socio-Economic Panel. In their analysis inequality increased to a smaller degree in the upper half of the wage distribution, but to a much larger degree in the lower half of the wage distribution.
Gernandt, J. and Pfeiffer, F. (2007),"Rising Wage Inequality in Germany" *SOEPpapers* 14, DIW Berlin, The German Socio-Economic Panel (SOEP).

[118] Goos, M. and Manning, A. (2007), "Lousy and Lovely Jobs: The Rising Polarization of Work in Britain", *Review of Economics and Statistics,* 89(1), 118-133.

III.3 Skill-biased Technical Change as the Cause of Rising Inequality

Since the 1990s a large literature has evolved which discusses increasing demand for high-skilled workers in the light of the increasing wage dispersion observed in the 1980s. Many researchers find the main reason to be technical progress which is not neutral but rather favors high-skilled labor (Katz and Murphy, 1992, Davis, 1992, Katz and Autor, 1999). The studies presented in the following focus on different aspects of the observed trends and on different hypotheses regarding the underlying forces which drive relative wage and employment shares. This selection of papers gives an outline of the general discussion of skill-biased technical change (SBTC) in the literature focusing on individual papers which analyze a certain key aspect of the literature. A focus will lie on those papers that analyze the SBTC hypothesis with emphasis on new ICT technology.

The universal observation of research on SBTC is that there has been an increasing relative demand for high-skilled workers. In a simply supply and demand framework, increasing relative wages and expanding employment of skilled workers is explained by shifts in the demand curve. For Europe a common observation is a decreasing relative wage and employment share of low-skilled workers and a simultaneous increase in the unemployment rate of these workers especially in the 1980s and 1990s. Thus many researchers analyze the data in supply and demand frameworks and try to locate where the shifts in demand are most pronounced. These shifts can happen between or within industries or skill groups. Between industry shifts are structural shifts, in which the aggregate employment or value added share of industries with a traditionally lower share of employment or compensation of high-skilled workers declines. Within industry shifts are shifts in relative wage or employment of high-skilled workers within individual industries.

A framework to analyze four candidate explanations for increases in the wage premium in the US was developed by Bound and Johnson (1992). The first explanation they propose is a trade deficit in the 1980s which may have shifted labor demand towards high-skilled workers. The second explanation is a decrease in wages of production workers in certain industries due to a decrease in union power. The third reason is skill-biased technological change, especially in the computer industry. The fourth possible explanation is a supply side argument linking inequality to a slowdown in the growth rate of the supply of high-skilled workers. The authors analyze these four possible explanations using a basic supply and demand framework with extensions for each candidate. They formulate changes in wages as a function of changes in technology, changes in labor supply, demand shifts and structural changes between industries (industry wage effects). For the analysis the authors use data from the Current Population Survey (CPS), which is a micro-level data set containing detailed information about workers. Data include information on wages and hours worked, as well as background information, such as education, potential experience, gender and race. After studying a range of different potential demand shifters, Bound and Johnson (1992) come to the conclusion that the most likely reason for the increasing education premium is SBTC and an increase in the general labor quality. Though the other factors play a role in the development, their influence is far smaller than the impact of SBTC.

Katz and Murphy (1992) studied wages in the US during the period 1963 to 1987. They distinguished between the level of education and unobservable skills of workers. Information about unobservable skills is retrieved from residual wages. The authors found an increase in the demand for skill already in the 1960s. The rising general inequality in wages started a decade later. The skill premium fluctuated across decades, increasing in the 1960s and 1980s while decreasing in the 1970s. In their more detailed analysis, using cells constructed from CPS data, the authors analyze the between- and within-sector-demand changes for different education and gender groups. A demand shift towards high-skilled workers is evident both between- and within-sectors. The former has taken place throughout the entire sample of 1967 to 1987 for workers of both genders. Within demand shifts started in the 1970s. Generally the demand shift for women has been larger due to the narrowing of the gender wage gap during this time. Furthermore the authors conclude that the movements in the college/high school wage differential reflect a changing relative price of college skills rather than in the relative skill of college educated workers.

While these studies documented significant movement in the wage shares of differently educated or skilled workers in the US, Krueger (1993)[119] asks the more specific question: can the observed change in relative wages can be attributed to the increasing computerization in the 1980s? The author (1993) augments CPS data for 1984 and 1989 with the High School and Beyond Survey (HSBS) for data on computer use and other personal information. He establishes an association of a computer wage premium with the education premium, which suggests complementarities between skilled or educated workers with computers. Workers who use a computer in the workplace have a wage premium of about 10 to 15 per cent. Analyzing different white collar wages, Krueger discovers a computer premium for all six analyzed groups. Considering the changes in the education wage premium for the high and low-skilled, he finds that a share of 0.3 to 0.5 of the observed changes between 1984 and 1989 is due to the computerization of the workplace. Thus he shows that SBTC, in form of an increase in computer usage and capital-skill complementarity, is an important factor behind the wage movements which are found by the authors mentioned above.

Davis (1992) also discusses different explanations for the development on the US labor market in an international context: international trade, changes in the relative supply of skilled workers and demand changes. SBTC seems to be a convincing reason for the increasing education wage differentials. Assuming that the technical change happens homogenously in advanced countries,

[119] Krueger, A.B. (1993), "How Computers Have Changed the Wage Structure: Evidence from Microdata, 1984-1989", *Quarterly Journal of Economics*, 10(1), 33-60.

Davis (1992) argues that this interpretation still lacks a convincing explanation why the evolution of relative wages continues to differ between countries. He argues that to be a convincing explanation SBTC has to be seen in connection with possible supply or institutional differences between countries. Additionally he stresses that clear evidence of SBTC is generally not observable and that this explanation is not directly in line with the finding that some of the countries considered have experienced little productivity and real wage growth.

Considering within-group wage changes Davis (1992) also found common trends of increasing inequality. This again may hint at SBTC as an underlying reason. Increasing inequality may show that there is some quality or skill of workers that is not directly observable by the level of education. In conclusion, Davis' (1992) findings hint at general SBTC as an explanation for the observed labor market developments, but he also stresses that there are differences for the analyzed countries. Thus it is not ultimately clear, from this analysis, whether SBTC is the main driving force of the recent wage developments and other factors such as institutions are slowing down this process for some countries or if there are other factors pushing wage inequality.

Similarly to Davis (1992), the OECD (1993) concluded that only a small part of the wage dispersion observed in most advanced countries is due to employment shifts between industries, while most of the changes can be found within industries. In all industries, a rising demand for highly educated workers can be observed for the 1980s. Additionally the OECD Employment Outlook (1993) discussed evidence of rising within group inequality. These analyses lead the authors to the conclusion that technical change which increases demand of educated workers may be a solid reason for the development at hand.

Berman et al. (1998)[120] investigate the influence of SBTC at an international level. Referring to the results from previous studies which claim that SBTC is the main driving force for the increasing skill premium and the worsening labor market performance of low-skilled workers Berman et al. (1998) argue that if SBTC is indeed taking place, then it should be observable in other advanced countries as well. As one would assume similar technical developments in all advanced countries, "pervasiveness" of SBTC is to be expected. Without observing similar trends in similar countries, the observed wage trends would more likely be due to institutions rather than to general non-factor-neutral technical progress. Under the assumption of pervasive SBTC and open economies within-industry skill upgrading is to be expected. Thus Berman et al. (1998) analyze whether there are similar within-industry shifts towards skilled workers and whether these shifts are concentrated in the same industries in various developed countries.

For their analysis Berman et al. (1998) examined twelve highly developed countries, indicated by the highest GNP per capita. They distinguish between high- and low-skilled workers by dividing the workforce into non-production and production workers, where the non-production

[120] Berman, E., Bound, J. and Machin, S. (1998), "Implications of Skill-Biased Technological Change: International Evidence", *Quarterly Journal of Economics*, 113(4), 1245-1279.

workers are assumed to be high-skilled. The data are taken from the United Nations General Industrial Statistics Database. This dataset covers 28 manufacturing industries for the relevant timeframe and the countries considered.

The authors find for a majority of the countries (7 out of 10) an increasing share of non-production workers while wages for these workers increased at the same time. Although the magnitude of the increase in demand for non-production workers differs across countries, Berman et al. (1998) claimed that these differences are a result of country specific institutions rather than a result of different levels of SBTC. Industries that have had the strongest influence on the total change of within-industry shifts towards non-production workers are electrical machinery, machinery and computers and printing and publishing. Berman et al. (1998) reach the conclusion that the increasing use of microprocessors has been the main driving force of SBTC in the 1980s in the advanced countries.

Similarly to Berman et al. (1998) Machin and Van Reenen (1998)[121] analyze as well whether there is persistent SBTC observable in advanced countries. In contrast to Berman et al. (1998) Machin and Van Reenen (1998) do not search for indirect evidence for SBTC, but directly test the effect of a technology indicator on wages of skilled workers. As a proxy for technological change, the authors use R&D expenditures[122] over value added. Furthermore they extend the analysis by not only considering non-production and production workers, but also by introducing an education based skill category.

Machin and Van Reenen (1998) analyze wages and technology for 15 industries within the manufacturing sector in France, Sweden, Denmark, Germany, Japan, UK, and the US. They extend the OECD STAN data set with data from the ANBERD and UNISD databases. In order to construct data for shares of high-skilled workers for each industry, they aggregated micro data on education levels from cross sectional data of the respective countries. Using this data, Machin and Van Reenen (1998) confirm the conclusion made by Berman et al. (1998) that most of the change in the non-production wage bill share has been observable within industries for the 7 advanced countries. In their econometric approach the authors estimate the effect of the ratio of R&D expenditures to value added on the non-production wage bill share as well as on the high-skilled employment share. Machin and Van Reenen (1998) find a positive effect of their technology proxy variable, R&D/Output, on wages and employment shares of high-skilled workers in all seven countries and thus conclude that skill upgrading is a common phenomenon. Nevertheless they also find differences in the degree of the effect. While they agree with former studies that in the 1980s the employment shares and wage bill shares of high-skilled workers have been rising the fastest in the US and the UK, they also find that in the US and the UK R&D

[121] Machin, S. and Van Reenen, J. (1998), "Technology and Changes in Skill Structure: Evidence from Seven OECD Countries", *Quarterly Journal of Economics*, 113(4), 1215-1244.

[122] R&D expenditures on the industry-level used by Machin and Van Reenen is taken from the STAN/ANBERD dataset and is defined as "the amount of R&D conducted by (but not necessarily financed by) the business sector". (Machin and Van Reenen, 1998, 1217)

exhibits the smallest effect on these shares. As an alternative to R&D expenditure as an indicator for SBTC, Machin and Van Reenen also apply computer usage across industries as an indicator in their analysis of the US and the UK. They find similar results and thus conclude that there are complementarities between computer usage and high-skilled labor.

Another approach is to model complementarity of skill and technology directly in the production function. Krusell et al. (2000)[123] incorporate capital-skill-complementarity in a macroeconomic analysis of SBTC. In the macroeconomic production function the authors include two types of capital, capital equipment and structure, and two types of labor, high-skilled and low-skilled. Capital equipment is chosen because its growth has been twice as high as the growth of capital structures or consumption since the 1970s, while at the same time the prices of capital equipment decreased significantly. Krusell et al. (2000) argue that although there has been a rising share of high-skilled workers entering the labor market the capital-skill-complementarity is strong enough to outweigh this negative effect on the skill premium. The model is fed with factor quantities and delivers the same trends that are observable in the US data: an increasing skill premium in the 1960s, a decreasing skill premium in the 1970s and an increasing skill premium thereafter. Over the sample period, the effect of the capital-skill-complementarity has increased the skill premium by 60 per cent, while the supply effects reduced the skill premium by 40 per cent. Overall Krusell et al. (2000) find capital-skill-complementarity to be the cause for most of the variation in the skill premium.

Acemoglu (2002)[124] takes up the issue of capital-skill-complementarity. He refers to a number of studies which claimed, as far back as in the early 20th century, that technical progress was seen to be skill-biased. Yet he also provides evidence that many key technological developments in the previous century, such as the programming of weaving machines, were rather skill replacing than skill favoring. Thus he asks why the 20th century should be characterized by skill-biased technical change. In a model of endogenous (directed) technical change, he argues that if there is a rising supply of skilled workers it may be worthwhile for a firm to invest in skill-favoring technology. Thus skill-biased technology is implemented and the skill premium increases.

In another study Acemoglu (2003)[125] employs the endogenous technological change framework to explain differences between the skill premia in the US and Europe. He argues that a shift in the demand for skilled workers which is similar in all countries cannot explain the differences between these countries. Thus he rejects simple supply and demand shifts as a reason for the observed differences in wage inequality. He suggests that wage compression found in many European countries due to labor market institutions plays a central role in explaining these cross-country differences. Faced with this compression firms are more likely to implement less-

[123] Krusell, P., Ohanian, L.E., Rios-Rull, J.V. and Violante, G.L. (2000), "Capital-Skill Complementarity and Inequaltity: A Macroeconomic Analysis", *Econometrica*, 68(5), 1029-1053.
[124] Acemoglu, D. (2002), "Technical Change, Inequality, and the Labor Market", *Journal of Economic Literature*, 40(1), 7-72.
[125] Acemoglu, D. (2003), "Cross Country Inequality Trends", *Economic Journal*, 113, 121-149.

skill-intensive technologies. Due to the higher wages of low-skilled workers, European firms will try to increase their productivity using technology which complements low-skilled workers. The effect of high-skill-complementary technology thus appears weaker than in the US.

Autor et al. (1998)[126] analyze the educational wage differentials in the US wage structure and their changes due to computerization. Similar to studies mentioned above they find that most inequality emerged within industries and see this as evidence for a demand shift towards high-skilled workers. The authors go further by asking what specific skills are demanded. They find a strong correlation between the increasing share of high-skilled workers and the growth of computer use within industries. Furthermore they assess which occupations are mainly affected by these developments. Autor et al. (1998) point out that a shift in the occupational mix was observable between 1979 and 1993 in those industries which experienced the highest growth in computer usage. This shift favored professionals and managers and was to the disadvantage of administrative occupations. Thus high-skilled workers seem to work in occupations which expand in the same industries where computer usage has grown the fastest. Within manufacturing industries one finds that one third of the within industry change of the high-skilled wage bill in the 1970s and 1980s can be explained by computer investments.

[126] Autor, D.H., Katz, L.F. and Krueger, A.B. (1998), "Computing Inequality: Have Computers Changed the Labor Market?", *Quarterly Journal of Economics*, 113(4), 1169-1213.

III.4 Changes of Skill Demand as Described by the "Task Approach"

The so-called "task approach" to the analysis of employment and wage inequality since 1980 was introduced by Autor et al. (2003)[127]. The authors take a closer look at the exact occupational characteristics of jobs that have experienced increasing demand in the course of computerization of workplaces. The authors try to go beyond indirect claims for why and how the proposing explanations for correlation between skill upgrading and increasing computer usage developed. They analyze the demand changes for specific skills between and within occupations. Thus they divide tasks of workers into the groups "routine" and "non-routine" tasks. It is assumed that routine tasks are more easily programmable and thus are substitutable by computers. In contrast, non-routine tasks can be complemented by computers. Routine tasks include for example record-keeping, calculating or assembly work. Non-routine task are for example managing, medical diagnosis or truck driving. The authors divide the categories further into cognitive, interactive and manual tasks. Calculating or medical diagnosis are cognitive tasks, while assembly work or truck driving are manual. Routine tasks are easily substitutable by computers and machinery. Autor et al. (2003) argue that many non-routine cognitive tasks such as hypothesis testing or forming are highly complemented by computers, whereas non-routine manual task are less complemented or substituted by computers.

Because prices of computers have decreased substantially over the past decades, the framework by Autor et al. (2003) suggests that workers performing routine tasks where more frequently substituted by computers. At the same time this increases the productivity of workers performing non-routine cognitive tasks as these are complemented by computer usage. Furthermore the authors argue that skilled workers have a comparative advantage in cognitive and interactive non-routine tasks. Thus as industries shift their occupational mix towards non-routine tasks as a result of the computerization of the workplace, the demand for skilled workers increases. Autor et al. (2003) therefore claim that skill upgrading is a result of a shift in tasks and a substitution of routine tasks by computers.

In fact, the authors show that in the 1970s to 1998 an increase in labor input of non-routine analytical and interactive tasks was observable, while at the same time, the share of routine tasks was decreasing. As these shifts were only observable after the 1960s, a connection between changes in the task structure and computerization seems likely, as the time frame coincides. Furthermore it is shown that most of the shifts were taking place within industries. This within industry development can largely be explained by computerization. These findings are persistent throughout industries for education-, gender- and age-occupational groups.

[127] Autor, D.H., Levy, F. and Murnane, R.J. (2003), "The Skill Content of Recent Technological Change: An Empirical Exploration", *Quarterly Journal of Economics*, 118(4), 1279-1333.

The mechanics of the task approach are well observable in the model of Autor et al. (2006)[128]. This theoretical analysis uses a simple Cobb-Douglas function with three inputs to exemplify the effect of increasing ICT use and its effect on the relative demand of high, medium and low-skilled workers and is briefly explained in the following. The authors define output as

$$Y = A^{\alpha} R^{\beta} M^{\gamma},$$

where A is the input of analytical tasks, R is the input of routine tasks and M the input of manual tasks. Labor for the analytical tasks is supplied by college graduates. Labor for the manual and routine tasks are supplied by high school graduates while routine tasks may also be performed by computers. Hence, computer and labor are perfect substitutes for this latter task category. Each high school worker *i* is endowed with a fraction of $\eta_i<1$ units of routine skills and one efficiency unit of manual skills. η is distributed continuously between zero and one. Thus, whether a worker supplies manual or routine tasks depends on the individual endowment of η and on the relative wage of routine work to manual work.

Autor et al. (2006) assume that the price for computer capital is decreasing. As computers and routine work are perfect substitutes, the price for one unit of computer capital must equal the wage rate for routine work. If the price of computers now decreases, the wage for routine workers will also decrease and more workers select themselves into manual jobs instead of routine jobs. This will lead to less employment in jobs with routine tasks and higher employment in jobs with manual tasks. While the wages for routine tasks will unambiguously decrease, it is not clear how the wages for manual tasks will react. There is a positive effect on wages due to the complementarity of the two inputs and a negative effect due to the increasing supply of workers. The college educated workers will profit from the increasing use of ICT as the supply of workers remains constant but their marginal product increases due to the complementarity of analytical tasks with routine tasks.

Assuming that workers specialized in routine tasks are medium-skilled and that workers specialized in manual tasks are low-skilled the predictions of the model mirror the observations of relative employment shares and relative income shares of all three educational groups in the US and also, as it will be described below, in Germany and the UK. While Autor et al. (2006) focus on the aggregate trends, these results also hold for changes of employment and income shares between and within occupations as shown by Autor et al. (2003). This implies a change in the skill demand for individual workers within their occupation.

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[128] Autor, D.H., Katz, L.F. and Kearney, M.S. (2006), "The Polarization of the US Labor Market", *American Economic Association Papers and Proceedings*, 96:22, 189-194.

Autor et al. (2008)[129] take a differentiated look at the US wage structure since the 1980s in the context of the task framework. The authors observe a rising wage inequality at the upper end of the wage distribution though at a slower pace in the 1990s and 2000s than in the 1980s. At the top of distribution, high-skilled workers have increased their relative pay compared to the rest of the workforce.[130] It is also claimed that the increase of wage inequality at the lower end of the wage distribution was specific to the 1980s and partly due to a decreasing (real) minimum wage. Apparently non-monotone demand shifts for high- and low-skilled workers working in non-routine settings have shaped the wage distribution. Thus Autor et al. (2008) argue that similar forces are at work as in the UK and Germany, where a polarization in employment is also occurring, albeit at a slower pace.

Instead of considering wages, Juhn et al. (2002)[131] analyze the unemployment rates in the United States between 1967 and 2000. Until the 1990s there was an especially deep decline in the employment rates of low- and least-skilled workers. In the 1990s the trend of inequality somewhat reversed at the lowest end, the 10th decile of the wage distribution, where inequality stopped rising. The authors attribute the trends in the employment shift for workers with different skills mostly to secular demand shifts. Although they do not state that these shift are driven by SBTC the observed unemployment trends are in line with the demand shift explanations put forward by Autor et al. (2008), especially regarding the least skilled workers.

Similar studies have been done for Great Britain and Germany. Goos and Manning (2007), analyzing data from the UK, emphasize that high skill and non-routine cognitive tasks go hand in hand. They argue that book keeping was always skill-intensive but is a routine task. Shelf filling on the other hand is regarded as low-skilled while it is a highly non-routine task. The authors claim that there has been a simultaneous increase in the demand for non-routine cognitive jobs which are well-paid and skill-intensive and in the demand for low-skilled non-routine manual jobs, which are low-paid. At the same time the demand for medium-paid jobs, routine medium-skilled, decreases as the workers are substituted by computers. The authors conclude that polarization in the employment structure is taking place.

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129 Autor, D.H., Katz, L.F. and Kearney, M.S. (2008), "Trends in US Wage Inequality: Revisiting the Revisionists", forthcoming in *Review of Economics and Statistics.*

130 Piketty and Saez (2004 and 2006) analyze the evolution of wages at the very top end of the income distribution. For the US, opposed to other countries such as Japan and France, a sharp rise in the relative wage share of the highest wage earners was observable over the last 30 years. As this wage increase is not persistent across countries, the authors propose social norms and the ability of high-level-earners to influence own earnings more directly as a very likely reasons for this increase and only attribute part of the influence to SBTC. Thus SBTC may enable "economic superstars" (Rosen 1981) to arise.
Piekett,T. and Saez, E. (2004), "Income Inequality in the United States, 1913-1998", *Quarterly Journal of* Economics, 118(1), 1-39.
Rosen, S. (1981) "The Economics of Superstars", *American Economic Review*, 71(5), 845-858.
Piekett,T. and Saez, E. (2006), "The Evolution of Top Incomes: A Historical and International Perspectives", *American Economic Review*, 92(2), 200-205.

131 Juhn, C., Murphy, K. M. and Topel, R.H. (2002), "Current unemployment, Historically Contemplated", *Brookings Papers on Economic Activity,* 1, 79-116.

Checking for between and within industry changes Goos and Manning (2007) find the increase of the share of professional and managerial jobs to be largely due to within industry changes. Manual routine occupations show negative between and within industry changes, suggesting substitution by computers and machinery as well as a structural shift towards the service sector. Analogously, routine clerical jobs display positive between changes and negative within changes. Low paid non routine jobs were confronted with a positive employment shift between and within industries.

Although polarization seems to be contradictory to the SBTC hypothesis, Goos and Manning (2007) show that skill upgrading has been taking place within occupations, even for the lower skilled workers. With regard to the argument that this is due to SBTC, the authors discuss a possible over-education of workers. If, due to the polarization of workers, some of the skilled workers are forced to work in lower paid jobs, they will increase the average educational attainment of this group. The authors conclude that the SBTC hypothesis is only true for the upper part of the wage distribution.

Spitz-Oener (2006)[132] and Dustmann et al. (2007) undertake similar studies for Germany. Spitz-Oener (2006) finds a large within change of occupational task requirements. Thus technical rather than structural change seems be the driving force. The author finds a substantial increase in non-routine cognitive tasks especially within industries that have a high growth of computer usage. The findings are robust within occupation- education- and age-groups. Generally Spitz-Oener (2006) finds similar developments for Germany as Autor et al. (2003) find for the US for the task categories, although wage dispersion is less pronounced in Germany. It is found that computerization pushed the employment share towards non-routine cognitive tasks and induced a substitution of routine tasks. Furthermore, most of the skill upgrading is explained by this task shift.

Although Spitz-Oener argues for a computer induced skill upgrading, she also finds similar polarization developments for Germany as Goos and Manning (2007) find for the UK. Dustmann et al. (2007) also find rising polarization in Germany. Instead of skill upgrading across all skill groups, the authors argue that workers at the upper and lower end of the wage distribution profited from increasing demand through technical change. Generally Dustmann et al. (2007) claim that the SBTC hypothesis may hold for the upper part of the wage distribution, while changes in the lower part are not as strong as predicted by SBTC but are largely explained by de-unionization and supply-shocks.

The literature and the data trends in different countries show that due to the introduction of advanced technology, especially ICT, production and organization has changed in the advanced countries. Understanding the underlying causes and their implications for different groups in

[132] Spitz-Oener, A. (2006), "Technical Change, Job Tasks and Rising Educational Demands: Looking Outside the Wage Structure", *Journal of Labor Economics*, 24(2), 235-270.

society may help to predict which groups will prosper through these developments and which groups will lose. The literature comes from estimating and evaluating the extent of demand changes to proposing which specific groups are affected in different ways by the technical change. After discussing what has already been studied in many developed countries, the next section describes possibilities for analyzing the effect of ICT on different skill groups in Europe.

III.5 The Influences of ICT on Working Conditions and Occupational Health

In the previous chapter the discussion about aggregate effects of ICT on relative employment and income shares has been reviewed. ICT is not only affecting task and skill demands, but it also changes the working conditions of individual workers. A worker has to fulfill different tasks compared to the time period prior to the computer revolution, but the day to day work routine and the working conditions have changed as well.

The changes in the working conditions can have positive or negative effects on health and safety of workers. The ICT-induced changes may be direct, by using an ICT device, or indirect through changing organizational structures which are made possible through ICT. Rantanen (1999)133 gives an overview of possible effects of ICT on workers' occupational health. As blue and white collar work becomes automated the tasks of workers change into setting, controlling, and analyzing these automated processes. Thus not only the job content changed but also the organizational structures adapt as ICT enables more flexible work patterns. Breshnahan et al. (2002)[134] discuss the correlation between ICT improvements and organizational change. They find that both are complementary to each other. Organizational change is captured by variables describing for example team work, pace of work or decision structures. Caroli and Van Reenen (2001)[135] describe the "productivity paradox" which states that potential productivity gains using ICT can only be realized if the organizational structure adapts to the new technology. In their analysis of French and British survey data Caroli and Van Reenen (2001) claim that complementarities between technological and organizational change exist but that these are due to data restrictions difficult to identify.

The introduction of ICT changed the competence demands in most occupations. In this context Rantanen (1999) names specific ICT-skills, communication skills, or skills needed to analyze and evaluate the work done by computers. Thus organizations have to change into learning-organizations. Within these organizations younger workers tend to cope better with the learning demands while older workers have more difficulties. Moreover Rantanen (1999) states that less educated workers also experience higher stress while working in an environment with ICT. Higher educated workers tend to experience higher job satisfaction by working with ICT, while medium and low-skilled workers experience more negative effects. Among these effects are higher job demands and increased workplace, which may be a positive or a negative challenge, lack of control over the work, computer problems or poor supervision, to name just a few. Complementarity of new organizational structures and skills are also described by Caroli and Van Reenen (2001). They claim that there exists a trade-off between advantages and drawbacks

[133] Rantanen, J. (1999), "Challenges for Occupational Health From Work in the Information Society", *American Journal of Industrial Medicine Supplement*, (1) p.1-6

[134] Breshnahan, T. F., Brynjolfsson, E. and Hitt, L. M. (2002), "Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm-Level Evidence", *Quarterly Journal of Economics*, Vol. 117, No. 1, pp.339-376.

[135] Caroli, E. and Van Reenen, J. (2001), "Skill-Biased Organizational Change? Evidence From a Panel of British and French Establishments", *Quarterly Journal of Economics*, vol. 116(4), pp. 1449-1492

for the workers when introducing new work programs. Skilled workers are expected to minimize the drawbacks relative to the advantages as they are assumed to be more able to cope with the innovations and experience job enrichment as opposed to stress and are less likely to make mistakes working on additional tasks. In addition to a skill bias Aubert et al. (2006)[136] find an age bias in technical and organizational change. Older workers are less likely to cope with innovative work practices and, regardless of their skill level, are more likely to be laid off compared to younger workers.

Askenazy and Caroli (2006)[137] perform an analysis of how new work practices and ICT have influenced workers' health and well-being in France. While they find that the introduction of new work practices such as quality norms, job rotations and work time flexibility are a cause of stress and enhance the sense of occupational risk, they also stress the positive effects of ICT which reduces the workers' sense of isolation and improves their safety. Thus, assuming that new work practices are enabled through improvements of ICT the innovations in ICT causes positive as well as negative effects for the workers occupational health and safety.

Askenazy and Corli (2006) describe three main new organizational practices: Total Quality Management, Just-in-time, and decentralized decision-making. Total Quality Management is introduced in order to facilitate constant improvement within the production process. Here ICT improves the information flow and enables easy feedback. Also customers may easily give feedback to the company. Just-in-time reduces delivery times and enables a quick reaction to market demands as well as reduces costs within the production process through less waste and less storage. Just-in-time profits directly from ICT innovations through instant feedback through enhanced communication mechanisms. Decentralized decision-making intents to involve different workers in a team's decision making and thus demands a high level of information flow. This may include job rotation which is also a characteristic of Just-in-time. Here workers are assigned to different tasks within the production and/or decision process.

These new work practices influence the working conditions of workers in various ways. Askenazy and Caroli (2006) summarize theories and findings concerning the effects on workers well-being in two blocks, one describing positive effects and one the downsides. Generally it may be assumed that the workers' health and safety is of major interest to the firm and is therefore a condition in the optimization procedure of the firm. In particular, save and healthy workers have lower absenteeism rates. The previously described organizational procedures are introduced in order to produce and sell more smoothly. Reducing safety concerns will most likely further smooth the process. Using ICT may further enable workers to receive help more quickly and to distribute information about possible safety and health measures more broadly. As workers may be involved in more parts of the production and decision process the worker may be more

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[136] Aubert, P., Caroli, E. and Roger, M. (2006), "New Technologies, Organisation and Age: Firm-Level Evidence", *The Economic Journal*, 116,pp. 73-93.
[137] Askenazy, P. and Caroli, E. (2006), "Innovative Work Practices, Information Technologies and Working Conditions: Evidence from France", *IZA Discussion Paper*, No 2321

motivated as work becomes more challenging in a positive way. This may raise interest in the workers' tasks and a positive feeling due to autonomy in the decision making.

Some of the negative effects of ICT use and changing organizational structures mentioned by Askenazy and Caroli (2006) are the following. While some may find it positively challenging to be on job rotation, this may also be an excessive demand for others. Similarly the pace of work increases and slack times which may be used to recover become less frequent. Also job rotation makes it more difficult to gain routine in a task and thus may decrease safety. Quality controls may also increase stress for the workers as they are more frequently monitored. This may also distract them from safety measures. Furthermore a less regular work schedule with irregular working times may have negative effects on the workers' well-being.

Rantanen (1999) also discusses direct effects of ICT on the workers health such as stress and physical problems arising from the long term use of computer technology. Among the latter are shoulder, neck or arm disorders. Nevertheless other hazardous working conditions may be taken over by machines based on computer technology. In that sense ICT can lead to more safety for the worker. Fairris and Brenner (2001)[138] take a closer look on Cumulative Trauma Disorders (CTD) of blue collar workers in the US. CTD results from repeated pressures, vibrations, or motions. They find some connection between CTD and new organizational structures such as total quality management and job rotation. They argue that CTD occur due to pressure on unconditioned muscles due to working in unfamiliar jobs, in job rotation routines or little recovery time in more efficient work practices. As ICT has an impact, positive as well as negative, on the health and safety of workers, an impact on the total job satisfaction of workers was denied by an analysis of Green and Tsitsianis (2004)[139]. They analyze the reasons for decreasing job satisfaction in Germany and Britain. Although they found some effects of new work practices described above on general job satisfaction, they found ICT to be without effect on the overall job satisfaction in both countries.

The papers described above draw a picture of how ICT influences the individual worker concerning health and safety. As the use of ICT increases firms have to reorganize work practices to make full use of the innovations. Thus workers have to adapt to the new technology and frequently learn new forms of applications, but are also faced with new working environments, such as working in teams, job rotation or quality management. The individual worker has advantages through these changes, but is also faced with new challenges and potentials hazards. Which and how strongly these different effects influence the worker's well-being depends on the skill-level and age of the worker as well as on the task content of the occupation. Thus, similar to the employment and compensation effects described before, ICT has distributional effects.

[138] Fairris, D. and Brenner, M. (2001), "Workplace Transformation and the Rise in Cumulative Trauma Disorders: Is There a Connection", Journal of Labor Research, 22, pp. 15-28.

[139] Green, F. and Tsitsianis, N. (2004), "Can the Changing Nature of Jobs Account for National Trends in Job Satisfaction?" *Studies in Economics 0406*, University of Kent

Skilled workers not only gain higher relative wages, but may also profit from more positive working conditions than less skilled workers due to ICT.

III.6 Data and Econometric Approach

In the former parts of this chapter the effects of ICT on workers with different skill levels have been analyzed. Skilled workers generally have gained through ICT when relative employment, relative compensation and working conditions such as health and safety are considered. The same mechanisms which lead to improvements for high-skilled workers let to worsening conditions of medium and low-skilled workers. This part of the chapter will discuss how this can be mirrored in an econometric framework in order to analyze these effects for Europe and other developed Countries.

The general task of this part of the report is to define the effects of ICT on employment in Europe with emphasis on the skill-based nature of ICT innovations. The literature on skill-biased technological change is concerned with this question in the most general way. Researchers have asked how ICT has influenced employment and compensation developments of skill groups relative to each other and thus tried to isolate the relative, distributional factor of ICT rather than the effects of ICT on total growth or productivity. Studies have been performed at individual and firm level, as well as industry and aggregate level. As in the other parts of the report, the industry level analysis is most suited for a cross-country analysis, as it allows for observational variation across industries and comparable data for many countries are readily available. Micro-level data is mostly not available in a comparable format for the EU 25 countries while macro-level data cannot say anything about structural changes (i.e. on industry level) or changes which occur within a country.

The second part of this chapter is concerned with a more complex analysis of the effects ICT has on changes in relative skill demand. This new strand of the literature has analyzed the changes ICT brought about in tasks of the worker. It poses the question of how the tasks content within and between occupations have changed due to ICT. Thus detailed information about the task content is needed for an econometric analysis. So far only studies for the US and Germany have been undertaken. Autor et al. (2003) merged the "Dictionary of Occupational Titles" of the US Department of Labor with micro-data from the Current Population Survey (CPS). Spitz-Oener (2006) who conducts a similar study for Germany, uses the "Qualification and Career Survey" from the German Federal Institute for Vocational Training and the Research Institute of the Federal Employment Service.

The third part discusses changing working conditions due to the use of ICT. It is found, through survey and case studies, that ICT has various effects on the individual worker. These effects can differ across workers with different skill levels. ICT has a direct effect on workers by using it and it affects the organizational structure. This is closely intertwined with the task theory as organizational changes will affect the task content of jobs. The studies mostly try to answer the question of how specific organizational alterations affect specific indicators of a workers' well-being. The surveys were done either for specific industries within a country or for a whole country such as the survey used by Askenazy and Caroli (2006) who use a Labor Force Survey with an additional survey on working conditions in France.

Judging from recent contributions to the literature described above, the task approach by Autor et al. (2003) appears to be the most appropriate model for analyzing effects of ICT on the skill-based employment and compensation effects of ICT (Autor et al., 2006, Spitz-Oener, 2006, Goos and Manning, 2007, Dustmann et al., 2007, Autor et al., 2008). To analyze the effects of ICT on specific occupations and the polarization on non-routine tasks at an international level, data on occupational skill requirements must be collected on a micro level for each country. Until now, appropriate data sets existed for only a subset of these countries. As authors have stressed, common technological change must be persistent in the skill upgrading and the skill requirements within occupations across countries (Berman et al. 1998[140], Katz and Autor 1999[141]). Thus a cross-country analysis for Europe would shed light on the underlying causes of employment and wage developments for the different occupation and skill groups. It is therefore highly recommended that the relevant data should be collected within the EU.

Nevertheless, interesting results may be derived in the light of the predictions of the task approach concerning the polarization of employment and wages by applying an econometric model with a translog share function similar to the model by Machin and Van Reenen (1998). This model indicates how relative employment and compensation of skill groups reacts to ICT capital within the production process. Thus data on relative employment and wage shares of skill groups, on output, capital and ICT capital is needed. Following the arguments made above and in the other chapters of the report industry level data would be most suited for the analysis.

The EU KLEMS dataset provides comparable data on wage and employment for three skill groups (high-, medium- and low-skilled), by gender and by age group for up to 30 industries for almost all EU25 countries as well for the US, Japan, Australia or South Korea. Furthermore it provides data on ICT-capital use for these countries. Thus the effect of ICT capital on wage shares and employment shares can be measured, controlling also for gender and experience. For cross-country analyses industry level data is probably the best data source, as it can provide in our case the most detailed data with homogenous data collection across countries.

Other cross-country analyses usually concentrate on manufacturing and/or distinguish between production and non-production workers only. In contrast to these studies the EU KLEMS data is a step forward, as skill classes are more detailed, derived from education levels and cover more sectors. As authors using the task approach show, different occupations and tasks are commonly fulfilled by high-, medium- or low-skilled (or educated) workers. Until data on the task content of occupations is available for all EU countries, share estimation with the EU KLEMS dataset might

[140] Berman, E., Bound, J. and Machin, S. (1998), "Implications of Skill-Biased Technological Change: International Evidence", *Quarterly Journal of Economics*, 113(4), 1245-1279.
[141] Katz L. F. and Autor, D. (1999), "Changes in the Wage Structure and Earnings Inequality", in O. Ashenfelter and D. Card, eds., "*Handbook of Labor Economics",* Elsevier, Amsterdam.

already highlight patterns common to EU countries or give information on which countries within the EU are confronted with different trends.

III.6.1 Proposed Model

The functional form proposed by Machin and Van Reenen (1998) is the high-skilled workers' wage bill share equation derived from a translog cost function.[142] Machin and Van Reenen use R&D expenditures as indicators for technological development. The proposed econometric specification is extended by ICT-capital (ICT/Y). This is a more direct measure for ICT development than R&D, which is desirable as the focus of interest lies on the effect of ICT on the development of high-skilled wage and employment changes. Furthermore, data on ICT-investment is available for roughly 30 industries in the EU KLEMS dataset, while data on R&D is available only for a fraction of these industries[143]. This approach is also in line with the econometric frameworks in the previous chapter which also use ICT/Y as the technology indicator. A discussion of ICT/Y versus R&D is presented in Section I.5.2 of this report. In order to compare the result and for the sake of completeness the estimation will also be performed with R&D/Y instead of ICT/Y as a proxy for technology.

The specification used by Machin and Van Reenen can be written with the new proxy variable as follows:

$$\Delta share_{it} = \alpha\Delta\log(K_{it}) + \beta\Delta\log(Y_{it}) + \gamma\log(ICT/Y)_{it} + \eta D_{it} + u_{it} \qquad \text{(III.1)}$$

$share_{it}$ is the share of total compensation of high-skilled workers in industry i at time t. Alternatively this may also be the share of total employment of the high-skilled workers. Y_{it} is the value added in industry i at time t in the relevant country and K_{it} denotes the respective capital stock[144]. We account for industry specific effects by time differencing, indicated by Δ. D_{it} is a set of time dummy variables. Adding time dummies controls for the effects of general macroeconomic fluctuations. Additionally industry specific time trends may be included to correct for the individual economic developments of each industry. Due to possible endogeneity issues relative wages are left out of the equation.[145] Dummies for gender- and age-groups can be included to control for gender- and experience-specific effects.

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[142] See Hamermesh (1993) for a general derivation of the share equation.
[143] Data on R&D is provided by the linked data base of the EU KLEMS in the form of R&D stocks. This is in contrast to Machin and Van Reenen (1998) who employ data on R&D expenditures. For Germany the dataset consists of data for 13 separate manufacturing industries and for the sectors "market services", "construction", "electricity, gas and water supply". The available industries and sectors can also be found in Table III.8. In order to account for the available aggregation levels of the separate variables the estimations with R&D are restricted to the four available sectors: manufacturing, market services,construction, electricity, gas and water supply.
[144] K_{it} is the Real fixed capital stock at 1995 prices including all assests.
[145] Machin and Van Reenen (1998) assume that relative wages move simultaneously in the business cycles while the changes in the levels are included in the time fixed effects. Fitzenberger and Franz (1998) estimate a similar model, but leave relative wages in the regression equation. They argue that considering

In the following, graphs (Figure III.1-5) of selected countries are shown indicating the trends of the share of total compensation and the share of total hours of different skill group between 1970 and 2005. The data is taken from the EU KLEMS dataset. The blue line shows the respective share of high-skilled workers, the red line the share of medium-skilled workers and the green line the share of low-skilled workers.

Figure III.1: Employment and compensation share in Austria

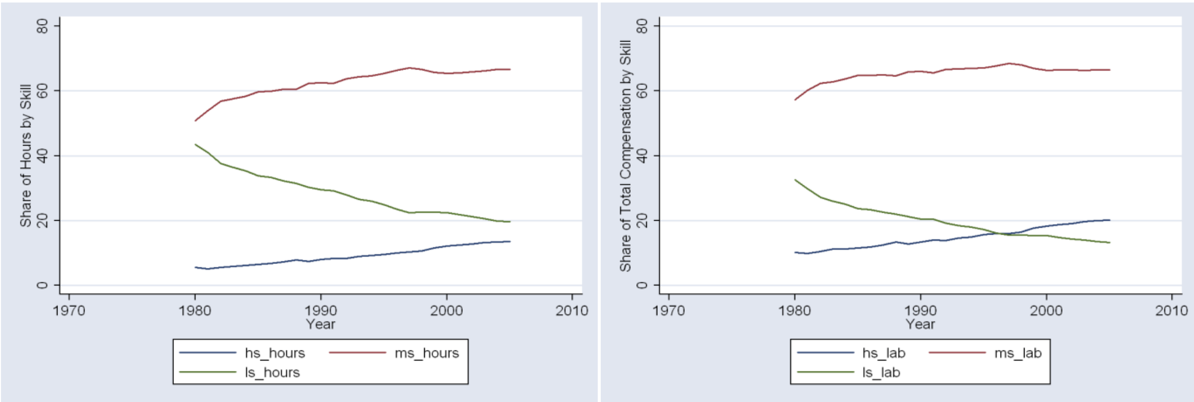
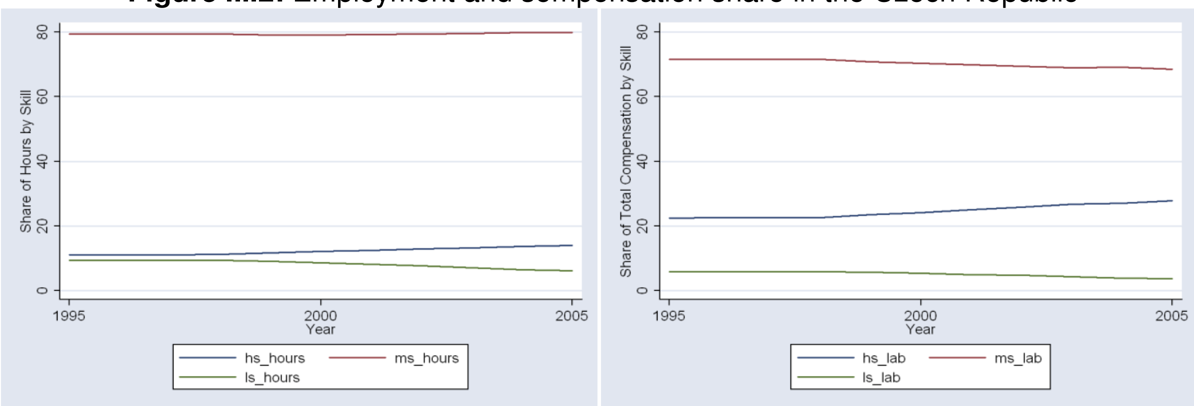


Figure III.2: Employment and sompensation share in the Czech Republic



the industry level, wages can be taken as exogenous. As an example they put forward collective bargaining agreements which signal wage levels to the other industries. In both articles the necessary development of suitable instruments for wages in these cost share regressions is emphasized.

Figure III.3: Employment (left) and compensation (right) share in Germany (after unification)

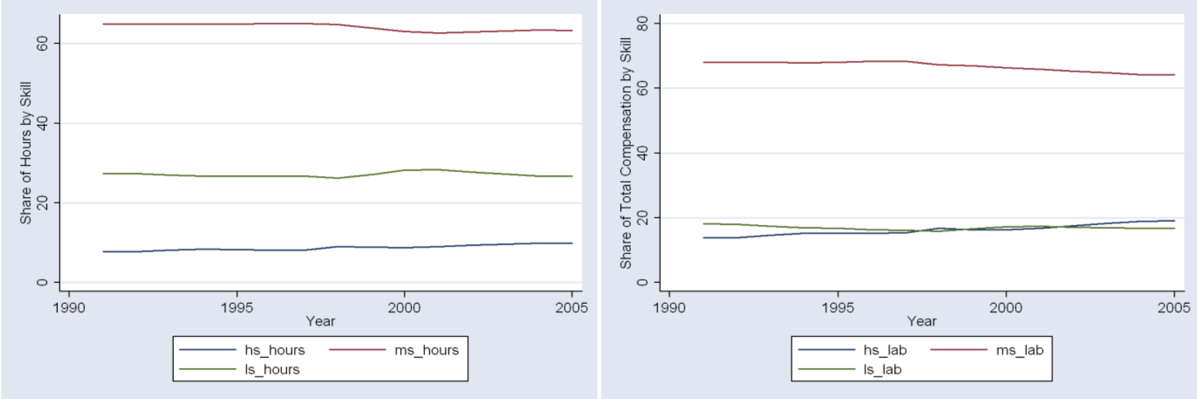


Figure III.4: Employment and compensation share in the Netherlands

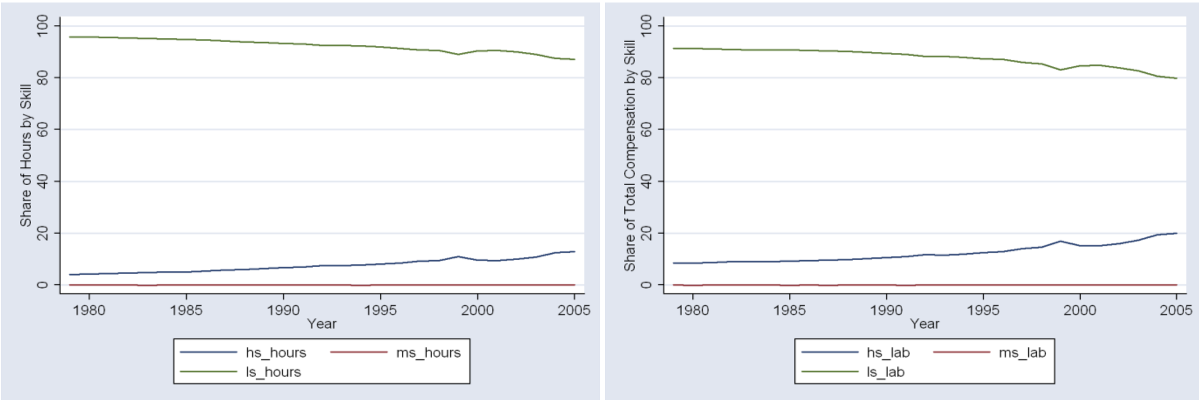
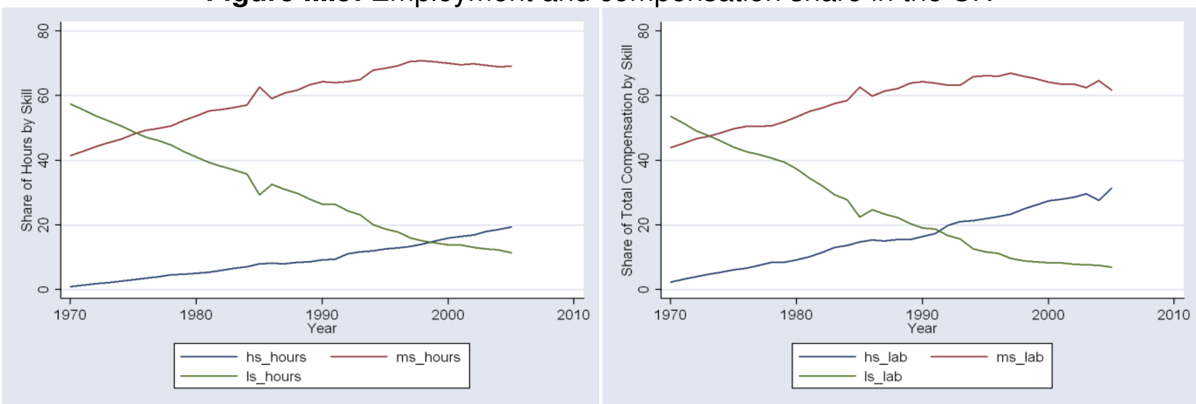


Figure III.5: Employment and compensation share in the UK



The graphs clearly show that high-skilled workers have gained substantially: both the employment share and the relative wage bill have increased. At the same time low-skilled workers lost relative to high-skilled workers. Their share of employment and total compensation has decreased in almost all industries in the countries considered, but the losses have moderated in recent years. Medium-skilled workers gained until the mid-1990s but their relative share in employment and total compensation has stagnated or decreased thereafter in all countries presented here. Our findings with EU KLEMS data are consistent with those of Spitz-Oener (2006), Goos and Manning (2007) and Dustmann et al. (2007) for Germany and the UK, confirming rising inequality in the upper tail of the wage distribution and less inequality in the lower tail of the distribution. The graphs also indicate that similar developments are observable in many EU countries simultaneously. An estimation using this data and the econometric approach proposed above may shed further light on the common European developments in wages and employment due to ICT.

III.6.2 EU KLEMS data and descriptive statistics for Germany

In this section, we use the EU KLEMS data for Germany and the proposed econometric model to exemplify the application of this mode of empirical investigation. Spitz-Oener (2006) and Dustmann et al. (2007) find a polarization of wages. Thus we would expect that relative wages of high-skilled workers increase, while the wage premium of medium-skilled worker relative to low-skilled workers should decrease. Table III.2 shows the high-skilled versus medium-skilled and medium- versus low-skilled wage differentials for Germany. Except of the small downshift at the turn of the century the skilled wage differential was continuously rising.

The EU KLEMS dataset provides data on shares of total compensation and total hours for three skill groups between 1991 and 2005. For these variables information on 14 industries are provided. The EU KLEMS dataset defines high-skilled workers as university graduates, medium-skilled as intermediate and low-skilled workers are without formal qualifications. Table III.2 displays the percentage change of the skilled wage differential for individual industries in the 2nd column.[146] Between 1991 and 1998 the relative wages of high-skilled workers increased in all industries. Between 1998 and 2005 in 11 out of 15 industries the skilled wage differential grew as well. According to Table III.2 the aggregate wage differentials between medium- and low-skilled (the relative wage of medium-skilled workers compared to low-skilled workers) increased until about 1997, stagnated and then decreased from 2000 onwards. Table III.2 shows that this is mostly driven by selected industries such as construction, where the wage differentials between medium- and low-skilled decreased by over 40% between 1998 and 2005. Similar trends can be observed if one considers the wage and employment shares of separate skill groups.

Table III.1 shows the changes in the compensation and employment shares of the different skill groups in the individual industries. To underline the trends, the backgrounds are marked green if the percentage change was positive for the employment share and the compensation share in the specific time frame for the respective skill group. The background is marked red if the share

[146] The wage differentials between medium- and low-skilled are the relative hourly wage between medium-skilled and low-skilled workers. The skilled wage differential is the relative hourly wage between high- and medium-skilled workers.

of total compensation and total hours decreased simultaneously. Evidently, high-skilled workers' share in total compensation and total hours worked increased in almost all industries over the whole period, only in some service industries the shares decreased. The opposite is true for medium-skilled workers. This skill group lost part of their shares to high and low-skilled workers in most industries. For most industries the loss was more pronounced in the second period, from 1998 to 2005. For low-skilled workers the results are mixed. The shares of total compensation and total hours of the low-skilled decreased in some industries and increased in others. Only in manufacturing and public administration, defense; and compulsory social security do shares decrease over the entire time frame. The drop in manufacturing is much lower between 1998 and 2005 than before. In all other industries the shares increased even at a higher rate between 1998 and 2005.

Similar trends become obvious when the share of total hours is seen next to the relative wages of the single skill groups in Table III.2. The increasing skilled wage differential for high-skilled workers in most industries shows that not only the shares of total compensation increased hand in hand with the share of total hours, but that the share of total hours increased although the hourly relative wage of high-skilled workers increased. For medium-skilled worker the share of hours worked decreased while the wage became relatively lower compared to high-skilled workers and even compared to low-skilled workers. The relative wage between medium-skilled and low-skilled workers decreased to the disadvantage of medium-skilled workers in most industries. The decrease has mostly been taken place after 1998. In industries, in which there is a positive growth rate of the wage differentials between medium- and low-skilled workers, the development is slowing down in the second period.

If the relative wage of a skill group increases and the share of total hours increases as well, this generally reflects a demand shift favoring this skill group. On the other hand if relative wages decrease and relatively fewer hours are worked this might be a result of a demand shift away from this skill group. In this light Table III.1 and III.2 underline the hypothesis that a polarization is taking place in Germany. Relative wages and employment of high-skilled workers have increased, while medium-skilled workers loose out in many industries as their relative wages and employment share decreased. The green and red blocks illustrate this dramatic development. Even the development of the low-skilled workers follows the prediction that there is no clear trend for their relative wages and employment. These results thus support the hypotheses of the task approach by Spitz-Oener (2006) and the findings of Dustmann et al. (2007).

Table III.1: Percentage changes in wage and employment shares of high-, medium- and low-skilled workers in Germany

Industry	Percentage changes of between years	Share of total hours of high-skilled workers	Share of total compensation of high-skilled workers	Share of total hours of med.- skilled workers	Share of total compensation of med.- skilled workers	Share of total hours of low-skilled workers	Share of total compensation of low-skilled workers
Total Industries	1991 - 1998	16.6	21.3	-0.2	-1.0	-4.3	-12.5
	1998 - 2005	5.2	9.4	-4.1	-5.4	8.4	12.9
Agriculture, Hunting, Forestry and Fishing	1991 - 1998	-8.3	5.2	-11.8	-7.3	36.8	27.0
	1998 - 2005	3.6	-6.1	-15.1	-12.6	29.1	39.2
Mining and Quarrying	1991 - 1998	36.5	32.2	10.6	5.4	-28.4	-29.8
	1998 - 2005	11.5	25.3	-3.9	-6.2	7.4	4.6
Total Manufacturing	1991 - 1998	26.5	26.5	3.9	2.0	-12.5	-17.2
	1998 - 2005	2.4	15.6	2.6	-1.3	-6.6	-6.3
Electricity, Gas and Water Supply	1991 - 1998	36.4	32.2	10.6	5.4	-28.4	-29.8
	1998 - 2005	11.5	25.3	-3.9	-6.2	7.4	4.6
Construction	1991 - 1998	8.4	20.9	1.0	-0.2	-3.5	-6.2
	1998 - 2005	8.8	10.6	-4.1	-7.8	9.5	28.1
Wholesale and Retail Trade	1991 - 1998	13.9	23.0	-1.2	-1.9	1.5	0.4
	1998 - 2005	5.8	9.9	-6.6	-8.7	14.6	35.0
Hotels and Restaurants	1991 - 1998	13.9	23.0	-1.2	-1.9	1.5	0.4
	1998 - 2005	5.8	9.9	-6.6	-8.7	14.6	35.0
Transport, Storage and Communication	1991 - 1998	-2.9	4.9	-0.6	0.6	2.0	-3.5
	1998 - 2005	16.4	21.0	-11.1	-10.5	27.8	34.6
Financial Intermediation	1991 - 1998	32.9	31.4	0.5	-2.0	-22.7	-22.6
	1998 - 2005	5.2	14.1	-1.7	-3.9	8.0	19.6
Real Estate, Renting and Business Activities	1991 - 1998	7.2	9.4	-2.8	-5.8	1.7	6.8
	1998 - 2005	-3.6	2.2	-5.6	-9.2	10.7	27.6

Public Admin, Defense; Compulsory	1991 - 1998	4.4	6.2	2.4	1.2	-10.7	-15.1
Social Security	1998 - 2005	10.5	-0.4	2.2	2.3	-15.7	-13.7
Education	1991 - 1998	7.5	8.2	-0.7	-3.5	-11.3	-20.0
	1998 - 2005	-1.1	1.8	-1.2	-4.1	6.4	16.0
Health and Social Work	1991 - 1998	-2.9	1.4	3.9	2.6	-10.7	-15.9
	1998 - 2005	-9.4	-6.5	-0.3	0.0	6.1	12.1
Other Community,	1991 - 1998	0.9	11.0	-6.3	-2.6	11.0	-5.0
Social and Personal Services	1998 - 2005	-11.8	-9.8	-6.9	-1.2	14.1	16.9
Private Households with	1991 - 1998	0.9	11.0	-6.3	-2.6	11.0	-5.0
Employed Persons	1998 - 2005	-11.8	-9.8	-6.9	-1.2	14.1	16.9

Data is with a green background if both, the wage and employment share increased for this group in the respective time frame. It is red if both decreased

.

Table III. 2: Percentage changes in employment shares of high-, medium- and low-skilled workers, skilled wage differential and wage differentials between medium and low-skilled in Germany.

Industry	Percentage changes of - between years	share of total hours worked by high-skilled workers	skilled wage differential	share of total hours worked by med.-skilled workers	wage differentials between medium- and low-skilled	share of total hours worked by low skilled workers
Total Industries	1991 - 1998	16.6	8.9	-0.2	17.9	-4.3
	1998 - 2005	5.2	9.2	-4.1	-9.9	8.4
Agriculture, Hunting, Forestry and Fishing	1991 - 1998	-8.3	11.4	-11.8	43.5	36.8
	1998 - 2005	3.6	-14.8	-15.1	-11.3	29.1
Mining and Quarrying	1991 - 1998	36.5	3.7	10.6	-8.3	-28.4
	1998 - 2005	11.5	29.6	-3.9	0.5	7.4
Total Manufacturing	1991 - 1998	26.5	3.9	3.9	10.5	-12.5
	1998 - 2005	2.4	31.7	2.6	-11.1	-6.6
Electricity, Gas and Water Supply	1991 - 1998	36.4	3.8	10.6	-8.3	-28.4
	1998 - 2005	11.5	29.6	-3.9	0.5	7.4
Construction	1991 - 1998	8.4	24.4	1.0	3.4	-3.5
	1998 - 2005	8.8	8.9	-4.1	-40.7	9.5
Wholesale and Retail Trade	1991 - 1998	13.9	13.9	-1.2	0.6	1.5
	1998 - 2005	5.8	8.8	-6.6	-27.5	14.6
Hotels and Restaurants	1991 - 1998	13.9	13.9	-1.2	0.6	1.5
	1998 - 2005	5.8	8.8	-6.6	-27.5	14.6
Transport, Storage and Communication	1991 - 1998	-2.9	13.8	-0.6	21.6	2.0
	1998 - 2005	16.4	5.8	-11.1	-11.8	27.8
Financial Intermediation	1991 - 1998	32.9	5.0	0.5	-4.6	-22.7
	1998 - 2005	5.2	35.9	-1.7	-22.6	8.0
Real Estate, Renting and	1991 - 1998	7.2	9.0	-2.8	-9.8	1.7
Business Activities	1998 - 2005	-3.6	15.4	-5.6	-23.9	10.7

Public Admin and Defense;	1991 - 1998	4.4	5.5	2.4	9.0	-10.7
Compulsory Social Security	1998 - 2005	10.5	-19.3	2.2	-4.8	-15.7
Education	1991 - 1998	7.5	10.2	-0.7	11.3	-11.3
	1998 - 2005	-1.1	15.1	-1.2	-15.8	6.4
Health and Social Work	1991 - 1998	-2.9	9.0	3.9	8.9	-10.7
	1998 - 2005	-9.4	4.3	-0.3	-9.1	6.1
Other Community,	1991 - 1998	0.9	8.1	-6.3	39.4	11.0
Social and Personal Services	1998 - 2005	-11.8	-4.9	-6.9	5.1	14.1
Private Households with Employed	1991 - 1998	0.9	8.1	-6.3	39.4	11.0
Persons	1998 - 2005	-11.8	-4.9	-6.9	5.1	14.1

Data is with a green background if the relative wage and the employment share increased for this group in the respective time frame. It is red if both decreased. The low-skilled employment share has green background if the relative wage of low-skilled workers and the employments increased in the same time period.

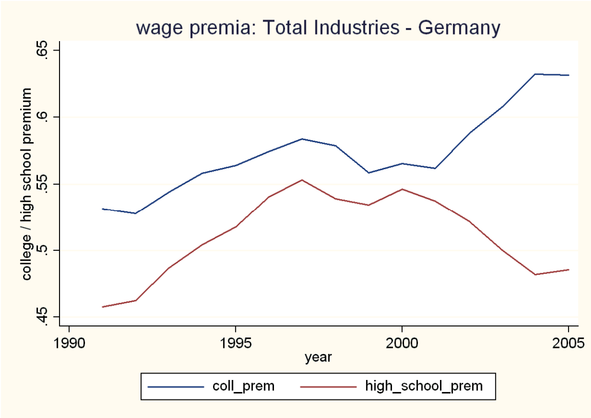


Figure III.6: High-skilled wage differentials

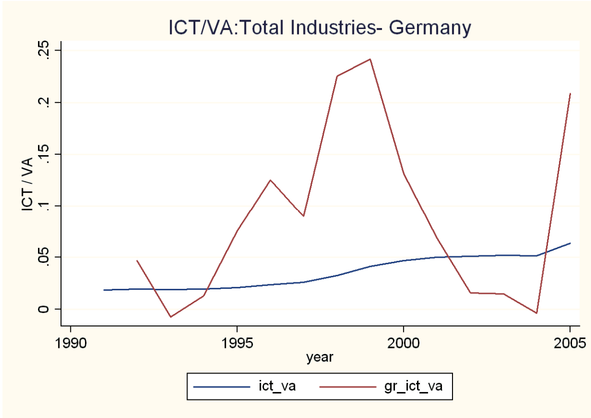


Figure III.7: ICT- Capital/Value Added, levels and growth rates for Germany

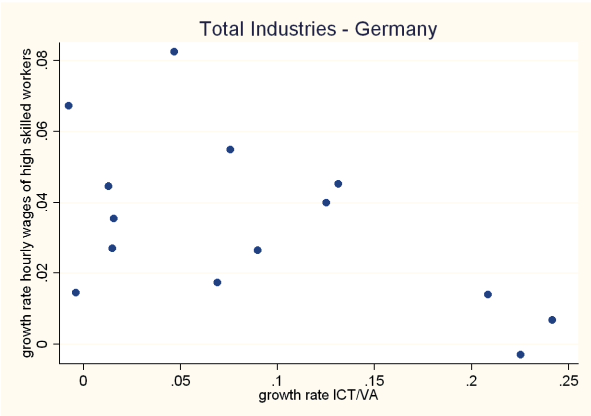


Figure III.8: Growth rates of hourly wages of high-skilled workers vs. growth rates of ICT- Capital/Value Added

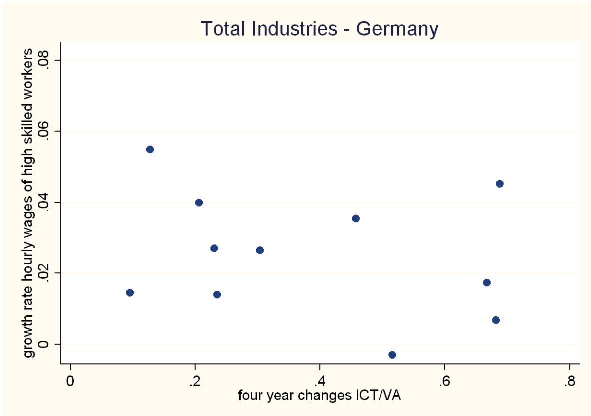


Figure III.9: Growth rates of hourly wages of high-skilled workers vs. four year changes of ICT- Capital/Value Added

Figure III.6-9: EU KLEMS, Germany, Total Industries, 1991 – 2005

Figure III.7 shows the evolution of ICT/Y in Germany in levels and growth rates from 1991 to 2005. ICT/Y is clearly increasing during this time frame with an increasing growth rate in the late 1990s. Figures III.8 and III.9 show scatter plots of the growth rate of hourly high-skilled wages and the growth rate of ICT/Y. Figure D has four year differences in the growth of ICT/Y. Table III.3 shows the correlations of the growth rate of the premium with the one period growth rate of ICT/Y. These graphs and the correlations do not show much evidence for ICT to be a driving force of high-skilled workers' wages. Although ICT/Y is increasing during the relevant time (figure III.7) the growth rate seem not closely to the growth rate of wages of high-skilled workers. In the next part this relationship is analyzed in more detail within the econometric framework.

Table III.3: Correlation between the growth rate of the skilled wage differential and the growth rate of ICT/Y for individual industries between 1991 and 2005 by industry

Industry	Correlation
Total Industries	-0.787***
Agriculture, Hunting, Forestry and Fishing	-0.057
Mining and Quarrying	-0.268
Total Manufacturing	-0.654**
Electricity, Gas and Water Supply	-0.124
Construction	-0.534**
Wholesale and Retail Trade	-0.278
Hotels and Restaurants	0.4741*
Transport, Storage and Communication	-0.238
Financial Intermediation	-0.115
Real Estate, Renting and Business Activities	-0.371
Public Admin and Defense; Compulsory Social Security	-0.482*
Education	-0.167
Health and Social Work	0.185
Other Community, Social and Personal Services	-0.394

***, **, *: statistically significant at 1, 5, and 10 % level, respectively; robust standard errors in parentheses

III.6.3 Estimation Results

Tables III.4 to III.7 present estimation results for the econometric specification described in Section 3.1, equation III.1 implemented using a panel of 15 manufacturing and service sectors in Germany covered by EU KLEMS dataset over the period 1991-2005. As was the case with the descriptive statistics, our data is taken from the EU KLEMS dataset. Definitions of ICT capital, value added and fixed capital correspond to those in Part I. Table III.4a shows estimation results for the share of total compensation of high-skilled workers as the dependent variable, while Table III.4b shows the estimation results when technology is proxied as the ratio of R&D to output. In Table III.5 the dependent variable is the share of total hours worked by high-skilled workers; Table III.5b again reports the results with R&D as the technology proxy. Analogously, Tables III.6 to III.7 assess the relationship for the respective shares of medium-skilled workers. Column (1) shows the results for estimating a specification along the lines of Machin and Van Reenen (1998) discussed in III.3.1. For columns (1) to (8) the endogenous variable is the first difference of the respective share. In the last column, (9), all variables are in levels. This regression is a fixed effects regression. Robust standard errors are reported in parentheses, with grouping by industry. Columns (10) to (15) repeat the main regressions using R&D instead of ICT as the technology variable.

The regression by Machin and Van Reenen (1998) is altered in several ways. The ICT proxy (ICT/Y) enters regressions (1) and (4) in level form as the ratio of ICT capital[147] to total real value added. In column (2), (3) and (5) the effect of the growth rate of this share is analyzed. In these regressions, value added and capital enter the equation as growth rates. The regressions are varied also by introducing time dummies and industry specific time trends. Columns (6) to (8) display the results of regressions where the effect of four year changes of the regressors are analyzed. The endogenous variable remains the first difference of the respective share.

For the most part, the results show a positive influence of ICT on the share of total compensation of high-skilled workers. If no year dummies are included and in case of four year changes the ICT coefficient turns negative. Including year dummies and industry specific time trends also turns the sign of the ICT proxy and thus implies a negative effect of ICT on the dependent variable. As shown in figure III.7 ICT/Y is increasing over time and thus may be correlated with the industry specific time effect. These industry trends and the year dummies already pick up most of the effect of ICT on employment shares. This may explain the negative sign and the low significance.[148] Using fixed effects shows a strong effect of ICT on the share which is also highly significant. In this case the explanatory power of the other variables is minimal.

Using R&D/Y as the technology proxy leads to less clear results. None of the regression specifications suggests that technology has a statistically significant effect on high skilled employment and compensation shares. This remains to be true even in the case where no time dummies are used. This can be due to much lower number of observations as only data for four sectors[149] were included in the regression. The period of time for which data on R&D is available is also much shorter than the corresponding period for data on ICT. Furthermore it seems that the correlation between ICT capital and R&D stock is quite heterogeneous across industries. To make the point Table III.8 shows the correlations between ICT/Y and R&D/Y for the available industries and sectors. Although the correlations are almost all significant, they switch between strong positive and strong negative correlations depending on the industry. Altogether ICT/Y seems to be the more direct and reliable technology proxy. In any case, the two regressions are not directly comparable since they rely on data for different time periods and different industries.

Value added has a clear negative effect on the high-skilled compensation share. This is in line with the results of Machin and Van Reenen (1998) who also obtain negative coefficients for the value added term, at least for some countries. Except for the fixed effects estimation fixed capital

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[147] The ICT variable used from the EU KLEMS is "real gross fixed capital formation" of ICT assets (Iq_ICT). This is also used in the previous estimations of this report (see Table I.12 in section I.6.1).
[148] A similar problem is already discussed in the empirical analysis of the effects of offshoring in Part II.
[149] The sectors used in this specification are Manufacturing, Construction, Electricity, Water and Gas Supply and Market Services. Data on R&D is only available on a less aggregated level for manufacturing in the EU KLEMS dataset. Therefore the estimations are restricted to these four sectors.

has also a positive effect on the compensation. Generally the significance levels of most of the coefficients are quite low.

Table III.5 displays the results for the regressions with the share of total hours worked by high-skilled workers taken as the dependent variable. Here the results are very similar to the ones with the share of total compensation. Only in one case a negative influence of ICT is observable. Again this is the estimation with industry specific time effects. The significance of the ICT coefficient in these regressions is also quite low. Thus it can be concluded that there seems to be a small effect of the ICT variable on the share of total compensation and the share of total hours of high-skilled workers.

In an additional exercise the availability of three different skill groups in the EU KLEMS data set was used. In order to study the polarization of the labor market which was observed by numerous authors, the medium-skilled shares are also analyzed. The estimations presented in Tables III.6 and 7a are analogous to Tables III.4 and 5, only with the medium-skilled workers' shares as the endogenous variables.

The results in Tables III.7 and 8 show that the ICT/Y has, as expected, a negative effect on the share of total compensation of medium-skilled workers in most regressions. Using the growth rates of one year and four year changes in ICT/Y, gives the expected negative result. In four out of six regressions with growth rates the respective coefficient is statistically significant. The coefficients of value added and capital have no clear sign.

Considering the share of total hours worked by medium-skilled workers the results are similar. ICT/Y growth rates are again all negative and if either both year dummies and time trends or no time corrections are included the coefficients are also highly significant. The coefficient estimates of value added and capital show no clear sign and depend very much on the estimation specification.

Overall, evidence from the EU KLEMS dataset and the econometric specification presented for Germany supports the hypothesis put forward by Spitz-Oener (2006), Dustmann et al. (2007), and Autor et al. (2008) that skilled biased technological change leads to a polarization of the labor market. Especially the strong effects for medium-skilled workers are consistent with more recent findings in the literature. The weaker results, especially for the high-skilled workers are most likely a result of the short data time series for Germany. The data for other countries are also more detailed on the industry level. Nevertheless it is known that the German labor market is less volatile. Institutions thus may prevent a strong effect of technical change of ICT on medium-skilled workers' hours worked. As a future step it would be interesting to repeat the exercise for other countries. As already mentioned, the data necessary is readily available.

Extending this exercise to other countries would shed light on the role of institutions. For instance, the labor market in the UK is arguably much less rigid than in Germany. Contrasting the results for Germany with results from the UK may therefore give interesting insights into the extent to which institutions interfere with the labor market effects of SBTC.

In conclusion it can be said, that in line with recent research, SBTC seems to characterize the data for Germany. The EU KLEMS dataset provides the opportunity to analyze the effect of ICT on relative employment and compensation on a European scale in comparison with the well analyzed US data. The proposed econometric model used with the EU KLEMS data can help to understand how ICT shapes the relative chances of high-, medium- and low-skilled workers in Europe. Furthermore it will be an important task to study how the effect of ICT differs across EU member countries. This seems likely given the different ICT penetration rates observed. As wage inequality is a highly debated topic in the economic literature and in every day press it might be very important to analyze the distributional effect ICT has in the European labor markets.

Table III.4a: Estimation results share equation, total compensation, high-skilled workers

	Share of total compensation of high-skilled workers								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ICT/Y	.827			-5.295					29.698***
	(1.076)			(3.456)					(7.40)
Δ ln(ICT/Y)		-.166	.444		.455				
		(.534)	(.397)		(.461)				
Δ 4 ln(ICT/Y)						.169	.054	.181	
						(0.53)	(.054)	(.393)	
VA									-5.13e-06
									(9.21e-06)
Δ ln Y	-2.36	-2.631**	-2.06	-2.379	-1.991				
	(1.503)	(1.075)	(1.465)	(1.493)	(1.474)				
Δ 4 ln Y						-.949	-1.071	-1.124	
						(.613)	(1.143)	(1.442)	
K									-3.60e-07
									(1.17e-06)
Δ ln K	.886	5.864*	.609	4.488*	2.053				
	(1.557)	(2.894)	(1.704)	(2.466)	(2.441)				
Δ 4 ln K						1.092	1.161	3.81	
						(.962)	(1.670)	(2.985)	
Year Dummies	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Industry Specific Time Trends	No	No	No	Yes	Yes	No	No	Yes	No
R^2	0.281	0.023	0.282	0.310	0.310	0.015	0.241	0.279	0.008
N	196	196	196	196	196	154	154	154	225

***, **, *: statistically significant at 1, 5, and 10 % level, respectively; robust standard errors in parentheses

Table III.4b: Estimation results share equation, total compensation, high-skilled workers
- R&D as proxy for technology

	Share of total compensation of high-skilled workers					
	(10)	(11)	(12)	(13)	(14)	(15)
R&D/Y	.217			-.215		
	(.107)			(.254)		
Δ ln(R&D/Y)		-.587	.207		-.216	
		(1.62)	(.809)		(.38)	
Δ 4 ln(R&D/Y)						-.014
						(1.5)
Δ ln Y	.963	-2.529	1.161	.561	.432	
	(.413)	(1.227)	(.258)	(.354)	(.477)	
Δ 4 ln Y						.547
						(.715)
Δ ln K	2.499	8.778*	1.791	-3.544	-2.618	
	(1.199)	(3.343)	(0.485)	(3.816)	(3.076)	
Δ 4 ln K						.426
						(.906)
Year Dummies	Yes	No	Yes	Yes	Yes	Yes
Industry Specific Time Trends	No	No	No	Yes	Yes	No
R^2	0.893	0.219	0.884	0.914	0.914	0.894
N	48	48	48	48	48	36

***, **, *: statistically significant at 1, 5, and 10 % level, respectively; robust standard errors in parentheses

Table III.5a: Estimation results share equation, total hours, high-skilled workers

	Share of total hours of high-skilled workers								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ICT/Y	.117			-2.137					17.742***
	(0.634)			(1.691)					(4.077)
Δ ln(ICT/Y)		0.278	.218		.254				
		(.220)	(.188)		(.215)				
Δ 4 ln(ICT/Y)						.121	.071	.232	
						(.104)	(.157)	(.205)	
Y									-7.58e-06
									(5.07e-06)
Δ ln Y	-.898	-.843	-.736	-.757	-.558				
	(.841)	(.515)	(.867)	(.830)	(.873)				
Δ 4 ln Y						-.294	-.459	-.335	
						(.297)	(.605)	(.717)	
K									-9.86e-08
									(6.45e-07)
Δ ln K	.322	2.097	.007	2.439	1.252				
	(.752)	(1.188)	(.789)	(1.582)	(1.51)				
Δ 4 ln K						.187	.465	1.858	
						(.298)	(.807)	(1.413)	
Year Dummies	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Industry Specific Time Trends	No	No	No	Yes	Yes	No	No	Yes	No
R^2	0.302	0.013	0.303	0.335	0.336	0.124	0.226	0.341	0.001
N	196	196	196	196	196	154	154	154	225

***, **, *: statistically significant at 1, 5, and 10 % level, respectively; robust standard errors in parentheses

Table III.5b: Estimation results share equation, total hours, high-skilled workers
- R&D as proxy for technology

	Share of total employment of high-skilled workers					
	(10)	(11)	(12)	(13)	(14)	(15)
R&D/Y	.085 (.037)			.334 (.265)		
Δ ln(R&D/Y)		-.264 (.819)	.129 (.387)		.911 (.988)	
Δ 4 ln(R&D/Y)						.128 (.118)
Δ ln Y	1.101 (.503)	-.818 (.708)	1.232** (.256)	1.141 (.573)	1.903 (.864)	
Δ 4 ln Y						1.044 (.814)
Δ ln K	.658 (1.18)	3.792 (1.784)	.311 (1.688)	1.229 (4.710)	.182 (3.864)	
Δ 4 ln K						-1.341 (1.264)
Year Dummies	Yes	No	Yes	Yes	Yes	Yes
Industry Specific Time Trends	No	No	No	Yes	Yes	No
R^2	0.707	0.137	0.703	0.714	0.914	0.706
N	48	48	48	48	48	36

***, **, *: statistically significant at 1, 5, and 10 % level, respectively; robust standard errors in parentheses

Table III.6a: Estimation results share equation, total compensation, medium-skilled workers

	Share of total compensation of medium-skilled workers								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ICT/Y	1.205			12.301*					-1.126***
	(3.201)			(6.598)					(.298)
Δ ln(ICT/Y)		-2.059***	-.737		-.819*				
		(.606)	(0.510)		(.452)				
Δ 4 ln(ICT/Y)						-1.126***	-.422	-.997**	
						(.298)	(.353)	(.395)	
Y									-1.368
									(1.182)
Δ ln Y	1.816	.783	1.189	2.282	1.537				
	(1.854)	(1.500)	(2.14)	(1.578)	(1.694)				
Δ 4 ln Y						-1.368	-1.094	-.532	
						(1.182)	(1.654)	(1.468)	
K									2.313
									(1.702)
Δ ln K	-3.882	-.853	-1.823	-11.098	-6.124				
	(7.059)	(4.134)	(7.388)	(9.748)	(10.193)				
Δ 4 ln K						2.313	1.571	-1.876	
						(1.702)	(2.729)	(4.580)	
Year Dummies	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Industry Specific Time Trends	No	No	No	Yes	Yes	No	No	Yes	No
R^2	0.247	0.095	0.251	0.352	0.349	0.122	0.264	0.381	0.145
N	196	196	196	196	196	154	154	154	225

***, **, *: statistically significant at 1, 5, and 10 % level, respectively; robust standard errors in parentheses

Table III.6b: Estimation results share equation, total compensation, medium-skilled workers
- R&D as proxy for technology

	Share of total compensation of medium-skilled workers					
	(10)	(11)	(12)	(13)	(14)	(15)
R&D/Y	.526			.361		
	(.453)			(.851)		
Δ ln(R&D/Y)		-4.95*	-4.928*		-4.489	
		(.1.769)	(1.789)		(2.926)	
Δ 4 ln(R&D/Y)						-1.292**
						(.289)
Δ ln Y	-.99	-5.236	-5.999**	-2.146	-6.642**	
	(1.562)	(2.823)	(1.249)	(.573)	(1.271)	
Δ 4 ln Y						-.648
						(1.29)
Δ ln K	-.574	1.238	4.906	2.404	-2.424	
	(5.899)	(2.969)	(3.755)	(8.452)	(4.103)	
Δ 4 ln K						.85
						(2.671)
Year Dummies	Yes	No	Yes	Yes	Yes	Yes
Industry Specific Time Trends	No	No	No	Yes	Yes	No
R^2	0.376	0.293	0.526	0.636	0.569	0.624
N	48	48	48	48	48	36

***, **, *: statistically significant at 1, 5, and 10 % level, respectively; robust standard errors in parentheses

Table III.7a: Estimation results share equation, total hours, medium-skilled workers

	Share of total hours of medium-skilled workers								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ICT/Y	1.483			7.193					27.132*
	(4.104)			(6.426)					(16.128)
Δ ln(ICT/Y)		-2.254***	-.44		-.51,6				
		(.645)	(.541)		(.469)				
Δ 4 ln(ICT/Y)						-1.064***	-.391	-.912**	
						(.323)	(.321)	(.329)	
Y									-5.55e-06
									(0.000)
Δ ln Y	.837	.025	.424	1.612	1.152				
	(1.403)	(1.613)	(1.559)	(.970)	(1.101)				
Δ 4 ln Y						-2.098 *	-1.938	-.846	
						(1.125)	(1.627)	(1.144)	
K									-1.54e-06
									(2.55e-06)
Δ ln K	-2.099	1.652	-.396	-6.703	-3.689				
	(9.148)	(5.095)	(9.630)	(12.581)	(12.919)				
Δ 4 ln K						3.333	2.847	-.119	
						(2.040)	(3.263)	(4.78)	
Year Dummies	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Industry Specific Time Trends	No	No	No	Yes	Yes	No	No	Yes	No
R^2	0.341	0.110	0.342	0.503	0.502	0.133	0.416	0.583	0.202
N	196	196	196	196	196	154	154	154	225

***, **, *: statistically significant at 1, 5, and 10 % level, respectively; robust standard errors in parentheses

Table III.7b: Estimation results share equation, total hours, medium-skilled workers

- R&D as proxy for technology

	Share of total employment of medium-skilled workers					
	(10)	(11)	(12)	(13)	(14)	(15)
R&D/Y	.529			.634		
	(.520)			(1.194)		
Δ ln(R&D/Y)		-6.156**	-5.627*		-6.675**	
		(1.689)	(1.862)		(1.862)	
Δ 4 ln(R&D/Y)						-1.369**
						(.348)
Δ ln Y	-.083	-8.306**	-6.293*	-1.095	-7.816**	
	(1.785)	(2.215)	(2.015)	(1.578)	(1.733)	
Δ 4 ln Y						-.387
						(2.017)
Δ ln K	-1.385	6.188	5.659	7.387	-.277	
	(6.849)	(4.213)	(4.082)	(13.472)	(7.295)	
Δ 4 ln K						.209
						(2.809)
Year Dummies	Yes	No	Yes	Yes	Yes	Yes
Industry Specific Time Trends	No	No	No	Yes	Yes	No
R^2	0.391	0.361	0.478	0.624	0.569	0.6490
N	48	48	48	48	48	36

***, **, *: statistically significant at 1, 5, and 10 % level, respectively; robust standard errors in parentheses

Table III.8: Correlation between the ICT/Y and R&D/Y for individual industries between 1991 and 2005 by industry

Industry	Correlation
Manufacturing	0.735***
Food, Beverages and Tobacco	0.915***
Textiles, Textile, Leather and Footwear	0.934***
Wood and of Wood and Cork	-0.683***
Pulp, Paper, Printing and Publishing	0.829***
Coke, Refined Petroleum and Nuclear Fuel	0.936 ***
Chemicals and Chemical Products	-0.821***
Rubber and Plastics	0.853***
Other Non-Metallic Mineral	0.827***
Basic Metals and Fabricated Metal	-0.922***
Machinery, Nec.	0.741***
Electrical and Optical Equipment	-0.521*
Transport Equipment	0.784***
Manufacturing Nec, Recycling	0.977***
Electricity, Gas and Water Supply	-0.839***
Construction	0.127
Market Services	0.943***

***, **, *: statistically significant at 1, 5, and 10 % level, respectively; robust standard errors in parentheses

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Appendix

Final Report - Annex

THE IMPACT OF ICT ON EMPLOYMENT

Contract 30-CE-0150922/00-65

with the European Commission-Directorate General Information Society and Media, Unit C1– “Lisbon Strategy and i2010”

Humboldt-Innovation GmbH

Coordinator: Prof. Michael C. Burda, Ph.D.
Humboldt-Universität zu Berlin
Institut für Wirtschaftstheorie II
Spandauer Straße 1
D-10099 Berlin, Germany
Tel: +49 30 2093 5638
burda@wiwi.hu-berlin.de

Date: 12/02/2009

HUMBOLDT-UNIVERSITÄT ZU BERLIN

Table A: Variables Analyzed, a Δ denotes first differences

Variable	**Definition**
lnN	logarithm of number of employees
lnw	logarithm of labour compensation
lnY	logarithm of gross value added (constant price)
t^2	square of time
$\hat{\epsilon}$	residual of the long run regression
RC	OECD Indicators of Regulation Impact (Section I.6.2)
epl	Employment Protection Legislation (Section I.6.3)
$\frac{I_{ICT}}{Y}$	ratio of ICT investment to output
$ICT\ TFP$	ICT Total Factor Productivity

Table B: Countries analyzed

Symbol	Country	Symbol	Country
Non Eu Countries		*New EU 10 countries*	
AUS	Australia	CYP	Cyprus
JPN	Japan	CZE	Czech Republic
KOR	South Korea	EST	Estonia
USA	United States of America	HUN	Hungary
EU 15	EU 15	LTU	Lithuania
EURO	Euro Zone	LVA	Latvia
EU 15 countries		MLT	Malta
AUT	Austria	POL	Poland
BEL	Belgium	SVK	Slovak Republic
DNK	Denmark	SVN	Slovenia
ESP	Spain		
FIN	Finland		
FRA	France		
GER	Germany		
GRC	Greece		
IRL	Ireland		
ITA	Italy		
LUX	Luxembourg		
NLD	the Netherlands		
PRT	Portugal		
SWE	Sweden		
UK	United Kingdom		

Table C: Summary Statistics for Sectoral Data: Germany and the US (1970-2005)

Variable	Obs	Mean	Std Dev.	Min	Max
Germany					
Y (in millions of Euros)	900	44,866	56,991	482	482,585
w (in Euros)	900	31,628	28,696	7,3034	325,391
N (thousands)	900	1069	829	482	482,586
$\frac{I_{ICT}}{Y}$ (in %)	350	3.18	0.29	0.04	17.7
USA					
Y (in millions of Dollars)	900	190,432	275,151	1,365	2,283,113
w (in Dollars)	900	38,257	22,010	2,687	243,155
N (thousands)	900	3,271	3,552	115	19,842
$\frac{I_{ICT}}{Y}$ (in %)	875	3.48	7.04	0.00	87.8

Table D: Industries analyzed

	SIC Code	Industry		SIC Code	Industry
agriculture	AtB	agriculture, hunting, forestry and fishing	electrical	30t33	electrical and optical equipment
mining	C	mining and quarrying	transporteq	34t35	transport equipment
food	15t16	food, beverages and tobacco	manufacturing	36t37	manufacturing nec; recycling
text	17t19	textiles, textiles, leather and footwear	electricity	E	electricity, gas and water supply
wood	20	wood and of wood and cork	construction	F	construction
pulp	21t22	pulp, paper, printing and publishing	sale	50	sale
coke	23	coke, refined petroleum and nuclear fuel	wholesale	51	wholesale trade
chemicals	24	chemical and chemicals	hotels	H	hotels and restaurants
rubber	25	rubber and plastics	transport	I	transport and storage and communications
othernonmetal	26	other non-metallic mineral	post	64	post and telecommunications
basicmetal	27t28	basic metals and fabricated metal	finance	JtK	finance, insurance, real estate and business services
machinery	29	machinery, nec	total	TOT	total industries

Table 1: Non-EU Countries and EU aggregates, Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	AUS	JPN	KOR	USA	EU15	EURO
	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$
Long Run Regression						
lnw	-0.95*	-0.91**	-0.85***	-0.98***	-0.80**	-0.77**
	(0.37)	(0.31)	(0.19)	(0.20)	(0.21)	(0.22)
lnY	0.73***	0.88***	0.72***	0.73***	0.71**	0.67***
	(0.05)	(0.16)	(0.15)	(0.08)	(0.09)	(0.10)
t^2	0.17	0.20	0.67*	0.34	0.06	0.08
	(0.20)	(0.22)	(0.29)	(0.20)	(0.17)	(0.18)
cons	1.59	0.24	1.83	2.45*	2.14	2.47
	(1.04)	(2.77)	(1.82)	(1.14)	(1.21)	(1.33)
R^2	0.78	0.70	0.72	0.84	0.85	0.82
ECM						
Δlnw	-0.45***	-0.04	-0.54***	-0.27***	-0.39***	-0.47***
	(0.07)	(0.04)	(0.08)	(0.07)	(0.06)	(0.09)
ΔlnY	0.44***	0.10*	0.73***	0.40***	0.59***	0.58***
	(0.11)	(0.05)	(0.06)	(0.05)	(0.08)	(0.09)
ϵ_{t-1}	-0.01	-0.01	-0.00	-0.01	0.05	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.09)	(0.09)
Δt^2	0.07	-0.39***	-0.37*	-0.32***	-0.01	-0.01
	(0.08)	(0.10)	(0.14)	(0.07)	(0.01)	(0.01)
cons	0.01*	0.02***	0.02	0.02**	-0.00	0.00
	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
R^2	0.41	0.12	0.61	0.30	0.44	0.46
N	875	800	875	875	875	875

***, **,*: statistically significant at 1, 5, 10 % level, respectively: robust standard error in brackets.

Table 2: EU 15 Countries, Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	AUT	BEL	DNK	ESP	FIN	FRA	GER	GRC	IRL	ITA	LUX	NLD	PRT	SWE	UK
	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$
Long Run Regression															
lnw	-0.49	-0.59	-0.57*	-0.82**	-0.53	-0.66**	-0.99***	-0.79***	-0.44	-0.80***	-0.73***	-1.04**	-0.95***	-0.86***	-0.78***
	(0.40)	(0.29)	(0.21)	(0.24)	(0.35)	(0.21)	(0.18)	(0.20)	0.23)	(0.15)	(0.18)	(0.30)	(0.19)	(0.18)	(0.10)
lnY	0.80***	0.69***	0.74***	0.78***	0.71***	0.81***	0.60***	0.31*	0.44***	0.54***	0.84***	0.97***	0.62***	0.75***	0.93***
	(0.11)	(0.11)	(0.10)	(0.13)	(0.09)	(0.04)	(0.13)	(0.13)	0.09)	(0.10)	(0.10)	(0.07)	(0.16)	(0.05)	(0.05)
t^2	-0.16	0.01	-0.02	0.11	-0.25	-0.05	0.22	0.40*	0.24	0.14	0.12	-0.01	0.27	0.05	-0.17
	(0.18)	(0.21)	(0.19)	(0.20)	(0.24)	(0.06)	(0.19)	(0.19)	0.22)	(0.18)	(0.18)	(0.13)	(0.29)	(0.12)	(0.09)
cons	-0.56	0.59	-0.26	0.73	0.30	0.26	3.60*	3.32*	1.34*	3.14**	-0.75	-0.27	1.99	1.37	-0.35
	(1.60)	(1.26)	(1.37)	(1.17)	(0.81)	(0.63)	(1.34)	(1.19)	0.51)	(1.10)	(0.54)	(0.96)	(1.07)	(0.97)	(0.60)
R^2	0.71	0.72	0.73	0.77	0.67	0.89	0.78	0.57	0.44	0.72	0.82	0.73	0.58	0.73	0.87
ECM															
Δlnw	-0.42**	-0.44***	-0.17***	-0.51***	-0.25***	-0.37***	-0.17*	-0.72***	-0.49***	-0.29**	-0.40*	-0.33	-0.44***	-0.18*	-0.14**
	(0.13)	(0.11)	(0.04)	(0.10)	(0.06)	(0.08)	(0.07)	(0.10)	0.08)	(0.10)	(0.17)	(0.20)	(0.08)	(0.09)	(0.04)
ΔlnY	0.29**	0.43**	0.24***	0.54***	0.40***	0.42***	0.33**	0.54***	0.32***	0.32**	0.40*	0.29	0.40***	0.15	0.36***
	(0.08)	(0.13)	(0.05)	(0.11)	(0.07)	(0.09)	(0.10)	(0.10)	(0.06)	(0.11)	(0.14)	(0.19)	(0.08)	(0.13)	(0.05)
ϵ_{t-1}	-0.01	-0.02*	-0.01	-0.01	-0.01	-0.01	-0.02	-0.01*	0.00	-0.02	-0.02*	-0.01	-0.01	-0.02	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Δt^2	-0.21*	-0.07	0.10	0.30***	-0.11	0.00	-0.00	0.19	0.27*	0.12	0.19	0.15	0.04	-0.06	0.07
	(0.07)	(0.14)	(0.11)	(0.07)	(0.12)	(0.07)	(0.18)	(0.19)	(0.11)	(0.17)	(0.22)	(0.12)	(0.11)	(0.10)	(0.09)
cons	0.02*	0.01	-0.00	-0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.02	0.00	0.00	0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)	0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
R^2	0.33	0.39	0.17	0.45	0.32	0.40	0.28	0.63	0.47	0.24	0.38	0.22	0.35	0.13	0.23
N	875	875	875	875	875	875	875.00	875.00	875	875	840	875	842	875	875

***, **,*: statistically significant at 1, 5, 10 % level, respectively: robust standard error in brackets.

Table 3: New EU 10 Countries, Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	CYP	CZE	EST	HUN	LTU	LVA	MLT	POL	SVK	SVN
	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$
Long Run Regression										
lnw	-0.54	-0.94***	-0.98***	-1.08***	-0.68**	-0.79***	-0.20	-0.76***	-0.71***	-1.09**
	(0.29)	(0.10)	(0.11)	(0.12)	(0.24)	(0.14)	(0.24)	(0.20)	(0.09)	(0.13)
lnY	0.67**	0.83***	0.72***	0.79***	0.70***	0.72***	0.68***	0.60***	0.86***	0.81**
	(0.20)	(0.07)	(0.06)	(0.06)	(0.10)	(0.07)	(0.11)	(0.10)	(0.05)	(0.05)
t^2	0.03	0.07	-0.05	0.12	-0.02	-0.21	0.10	-0.13	-0.21	0.14
	(0.20)	(0.09)	(0.27)	(0.14)	(0.37)	(0.21)	(0.11)	(0.23)	(0.15)	(0.09)
cons	-0.28	0.64	1.38**	2.38***	0.35	0.56*	-0.95	2.36	-0.78	0.60
	(0.80)	(0.64)	(0.43)	(0.58)	(0.78)	(0.21)	(0.48)	(1.28)	(0.40)	(0.34)
R^2	0.60	0.86	0.85	0.88	0.79	0.83	0.73	0.76	0.91	0.85
ECM										
Δlnw	-0.49***	-0.16**	-0.71***	-0.46***	-0.59***	-0.24***	-0.27**	-0.14**	-0.45***	-0.24*
	(0.07)	(0.05)	(0.07)	(0.05)	(0.07)	(0.06)	(0.07)	(0.04)	(0.03)	(0.11)
ΔlnY	0.54***	0.19***	0.51***	0.36***	0.44***	0.29***	0.14***	0.17*	0.42***	0.26**
	(0.10)	(0.04)	(0.05)	(0.07)	(0.07)	(0.06)	(0.03)	(0.07)	(0.04)	(0.07)
ϵ_{t-1}	-0.00	-0.06*	-0.04	-0.08**	-0.05	-0.07*	-0.04	-0.05	-0.05	-0.02
	(0.01)	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)
Δt^2	0.06	0.97	1.05	2.61***	1.26	1.06	-0.37	-1.47**	-1.41*	1.09*
	(0.81)	(0.66)	(0.93)	(0.68)	(1.23)	(1.46)	(0.71)	(0.43)	(0.56)	(0.43)
cons	0.00	-0.07	-0.07	-0.15***	-0.06	-0.06	0.04	0.08*	0.08*	-0.07*
	(0.05)	(0.04)	(0.06)	(0.04)	(0.08)	(0.09)	(0.04)	(0.03)	(0.04)	(0.03)
R^2	0.55	0.18	0.65	0.39	0.52	0.26	0.27	0.25	0.72	0.16
N	246	250	250	325	240	250	249	250	250	250

***, **,*: statistically significant at 1, 5, 10 % level, respectively: robust standard error in brackets.

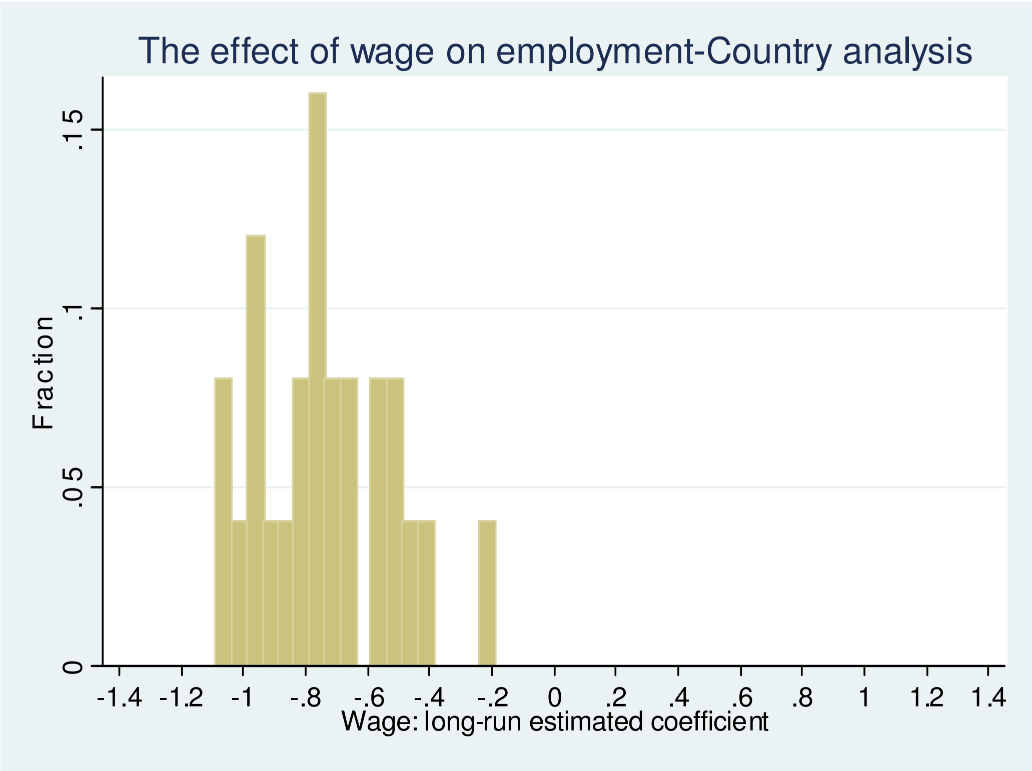

Figure 1: The effect of wage on employment.

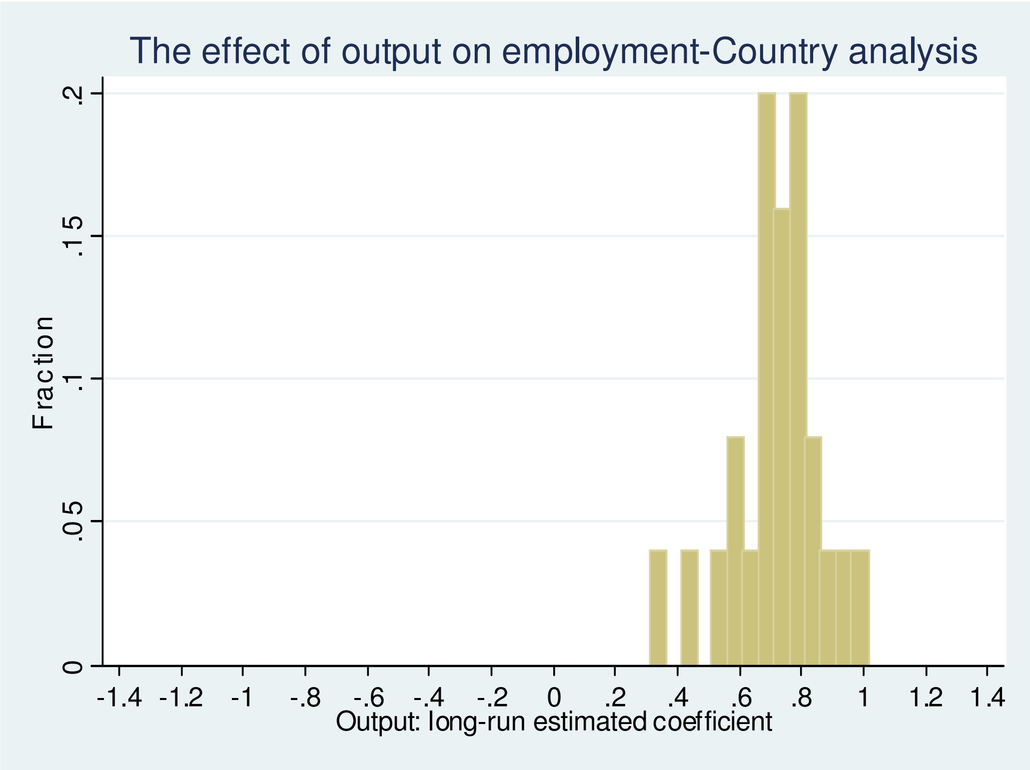

Figure 2: The effect of output on employment.

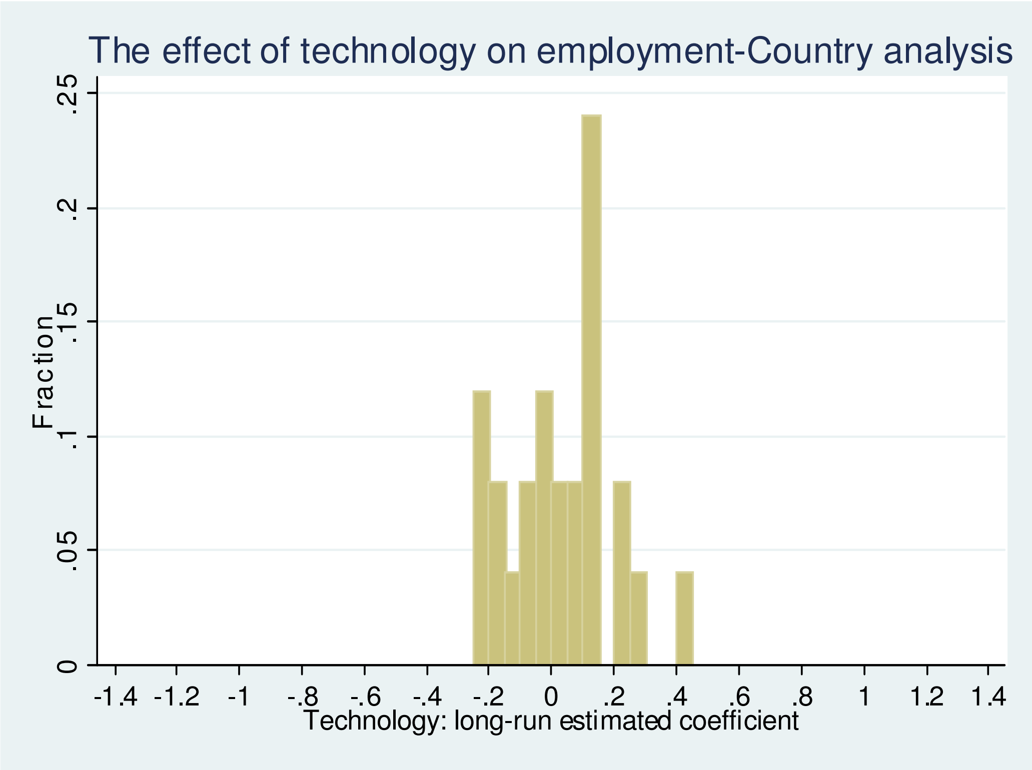

Figure 3: The effect of technology (t^2) on employment.

Table 4: Non-EU Countries and EU Aggregates, Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	AUS	JPN	KOR	USA	EU15	EURO
	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$
Long Run Regression						
lnw	-0.90***	-0.79***	-1.04***	-1.05***	-1.08**	-1.09***
	(0.03)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)
lnY	1.00	1.00	1.00	1.00	1.00	1.00
	.	.	.	.	.	.
t^2	-0.05*	0.03	0.19***	0.14***	0.02**	0.03***
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
cons	-0.81***	-2.66***	-0.44***	-0.56***	-0.33**	-0.30***
	(0.12)	(0.20)	(0.12)	(0.07)	(0.05)	(0.04)
ECM						
Δlnw	-0.45***	-0.04	-0.56***	-0.29***	-0.41***	-0.49***
	(0.07)	(0.04)	(0.07)	(0.07)	(0.05)	(0.09)
ΔlnY	0.45***	0.11*	0.73***	0.41***	0.60***	0.59***
	(0.11)	(0.05)	(0.06)	(0.05)	(0.10)	(0.12)
ϵ_{t-1}	-0.04***	-0.02*	-0.10***	-0.06***	0.06	0.02
	(0.01)	(0.01)	(0.02)	(0.01)	(0.12)	(0.12)
Δt^2	0.07	-0.38**	-0.27	-0.30*	-0.06***	-0.08***
	(0.14)	(0.13)	(0.21)	(0.12)	(0.01)	(0.02)
cons	0.01*	0.02***	0.02	0.02***	-0.00	0.00
	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
R^2	0.42	0.11	0.63	0.33	0.46	0.48
N	875	800	875	875	875	875

***, **,*: statistically significant at 1, 5, 10 % level, respectively: robust standard error in brackets.

Table 5: EU 15 Countries, Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	AUT	BEL	DNK	ESP	FIN	FRA	GER	GRC	IRL	ITA	NLD	PRT	SWE	UK
	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$
Long Run Regression														
lnw	-0.86***	-0.98***	-0.86***	-1.02***	-1.03***	-0.89***	-0.92***	-1.04***	-0.97***	-0.99***	-0.81***	-0.76***	-0.97***	-0.68***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)
lnY	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	.	.	.	.	.	.	.	.	.	.	.	.	.	.
t^2	-0.16***	0.08***	0.04**	0.02	-0.12***	-0.06***	0.04***	0.10***	-0.06**	-0.06***	-0.10***	-0.10**	-0.07***	-0.26***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.03)	(0.01)	(0.02)
cons	-0.82***	-0.64***	-1.16***	-0.56***	-0.36***	-0.93***	-0.78***	-0.78***	-0.97***	-0.72***	-1.19***	-0.97***	-0.42***	-1.30***
	(0.06)	(0.05)	(0.11)	(0.06)	(0.07)	(0.04)	(0.07)	(0.05)	(0.06)	(0.07)	(0.08)	(0.08)	(0.09)	(0.07)
ECM														
Δlnw	-0.43**	-0.45***	-0.17***	-0.51***	-0.27***	-0.38***	-0.19*	-0.72***	-0.49***	-0.30**	-0.33	-0.45***	-0.20*	-0.16***
	(0.14)	(0.11)	(0.04)	(0.09)	(0.07)	(0.08)	(0.07)	(0.10)	(0.07)	(0.10)	(0.19)	(0.07)	(0.08)	(0.04)
ΔlnY	0.29**	0.45**	0.26***	0.54***	0.42***	0.43***	0.36**	0.55***	0.32***	0.34**	0.32	0.41***	0.16	0.37***
	(0.08)	(0.13)	(0.05)	(0.11)	(0.07)	(0.09)	(0.12)	(0.10)	(0.06)	(0.12)	(0.16)	(0.08)	(0.12)	(0.05)
ϵ_{t-1}	-0.02	-0.08*	-0.03*	-0.04**	-0.06*	-0.04**	-0.08***	-0.00	-0.00	-0.02	-0.11***	-0.03***	-0.08**	-0.05*
	(0.02)	(0.04)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.03)	(0.01)	(0.02)	(0.02)
Δt^2	-0.21*	-0.03	0.10	0.30**	-0.11	-0.01	-0.00	0.19	0.27*	0.11	0.11	0.02	-0.07	0.05
	(0.08)	(0.17)	(0.13)	(0.10)	(0.16)	(0.08)	(0.21)	(0.19)	(0.10)	(0.16)	(0.17)	(0.13)	(0.13)	(0.10)
cons	0.02*	0.01	-0.00	-0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.01	-0.01
	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
R^2	0.33	0.40	0.18	0.45	0.34	0.41	0.28	0.63	0.47	0.21	0.31	0.35	0.16	0.25
N	875	875	875	875	875	875	875	875	875	875	875	842	875	875

***, **,*: statistically significant at 1, 5, 10 % level, respectively: robust standard error in brackets.

Table 6: New EU 10 Countries, Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	CYP	CZE	EST	HUN	LVA	MLT	POL	SVK	SVN
	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$
Long Run Regression									
lnw	-0.61***	-0.95***	-0.71***	-0.89***	-0.39***	-0.91***	-0.82***	-0.75***	-0.84***
	(0.04)	(0.05)	(0.07)	(0.05)	(0.04)	(0.10)	(0.05)	(0.04)	(0.06)
lnY	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	.	.	.	.	.	.	.	.	.
t^2	-0.07*	-0.02	-0.40***	-0.15***	-0.66***	0.22***	-0.32***	-0.33***	-0.15***
	(0.03)	(0.04)	(0.06)	(0.04)	(0.05)	(0.04)	(0.05)	(0.05)	(0.04)
cons	-1.48***	-1.12***	-1.25***	-1.12***	-0.58***	-1.11***	-0.77***	-1.76***	-0.67***
	(0.07)	(0.22)	(0.23)	(0.29)	(0.05)	(0.15)	(0.12)	(0.20)	(0.09)
ECM									
Δlnw	-0.51***	-0.24***	-0.70***	-0.47***	-0.24***	-0.29**	-0.18***	-0.49***	-0.34**
	(0.07)	(0.05)	(0.06)	(0.06)	(0.05)	(0.08)	(0.04)	(0.03)	(0.10)
ΔlnY	0.61***	0.28***	0.57***	0.39***	0.44***	0.19***	0.24**	0.48***	0.36***
	(0.10)	(0.04)	(0.07)	(0.07)	(0.07)	(0.05)	(0.07)	(0.03)	(0.06)
ϵ_{t-1}	-0.24***	-0.22***	-0.12*	-0.19***	-0.34**	-0.12*	-0.21***	-0.23***	-0.30***
	(0.05)	(0.03)	(0.05)	(0.03)	(0.09)	(0.04)	(0.03)	(0.05)	(0.04)
Δt^2	0.00	0.85	0.98	2.49*	0.68	-0.26	-1.07	-0.97	0.60
	(0.59)	(0.71)	(0.97)	(1.09)	(1.72)	(0.79)	(0.69)	(0.61)	(0.67)
cons	0.01	-0.06	-0.07	-0.15*	-0.05	0.04	0.06	0.06	-0.04
	(0.04)	(0.04)	(0.06)	(0.06)	(0.11)	(0.04)	(0.04)	(0.04)	(0.04)
N	246	250	250	325	250	249	250	250	250
R^2	0.62	0.27	0.66	0.43	0.37	0.24	0.32	0.75	0.39

***, **,*: statistically significant at 1, 5, 10 % level, respectively: robust standard error in brackets.

Table 7: EU Countries (1st Part), Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	AUT			DNK			ESP			FIN		
	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Long Run Regression												
lnw	-1.05***	-0.47	-1.09***	-1.04***	-0.59*	-1.16***	-1.36***	-0.73*	-1.28***	-0.89***	-0.59	-0.97***
	(0.10)	(0.45)	(0.11)	(0.12)	(0.28)	(0.15)	(0.12)	(0.27)	(0.19)	(0.12)	(0.37)	(0.15)
lnY	1.07***	0.80***	1.09***	0.99***	0.77***	0.99***	0.87***	0.79** *	0.90***	0.90***	0.73***	0.90***
	(0.05)	(0.11)	(0.05)	(0.05)	(0.10)	(0.04)	(0.06)	(0.11)	(0.07)	(0.06)	(0.07)	(0.06)
RC	-0.33*		-0.40*	-0.15		-0.17	-0.05		-0.21	-0.32**		-0.34*
	(0.12)		(0.18)	(0.10)		(0.12)	(0.14)		(0.15)	(0.09)		(0.12)
t^2	-0.28**	-0.12	-0.28*	-0.17*	0.04	-0.10	0.37**	0.21	0.33*	-0.37**	-0.32	-0.30*
	(0.09)	(0.18)	(0.10)	(0.07)	(0.21)	(0.09)	(0.10)	(0.19)	(0.12)	(0.10)	(0.19)	(0.11)
epl		0.01	0.04		0.04*	0.03		0.02	0.00		0.03	-0.02
		(0.02)	(0.02)		(0.02)	(0.02)		(0.02)	(0.01)		(0.02)	(0.02)
cons	-0.55	-0.73	-0.64	0.03	-0.60	0.56	1.38**	0.21	0.90	0.10	0.25	0.38
	(0.45)	(1.87)	(0.49)	(0.63)	(1.57)	(0.71)	(0.43)	(0.99)	(0.42)	(0.34)	(0.93)	(0.31)
R^2	0.96	0.74	0.96	0.95	0.75	0.96	0.94	0.79	0.93	0.92	0.74	0.93
ECM												
Δlnw	-0.14	-0.30**	-0.16*	-0.25**	-0.16**	-0.25**	-0.29**	-0.50***	-0.25*	-0.13*	-0.19**	-0.14*
	(0.07)	(0.09)	(0.07)	(0.08)	(0.05)	(0.08)	(0.09)	(0.12)	(0.11)	(0.05)	(0.06)	(0.05)
ΔlnY	0.15*	0.18**	0.13	0.26**	0.19***	0.21*	0.31*	0.52***	0.31*	0.28***	0.34***	0.26***
	(0.06)	(0.06)	(0.07)	(0.08)	(0.05)	(0.07)	(0.11)	(0.14)	(0.10)	(0.04)	(0.06)	(0.03)
ΔRC	-0.49***		-0.52**	-0.10		-0.08	-0.02		-0.01	-0.15		-0.03
	(0.11)		(0.14)	(0.05)		(0.05)	(0.08)		(0.09)	(0.12)		(0.12)
Δt^2	-0.27*	-0.07	-0.21	-0.19*	-0.26	-0.51***	0.73***	0.57	0.86**	-0.07	0.07	0.12
	(0.10)	(0.13)	(0.16)	(0.08)	(0.20)	(0.11)	(0.12)	(0.28)	(0.22)	(0.17)	(0.19)	(0.28)
ϵ_{t-1}	-0.01	-0.01	-0.01	-0.06***	-0.00	-0.08***	-0.02	-0.01	-0.02	-0.04	-0.00	-0.03
	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)
Δepl		-0.01*	-0.02***		-0.01	-0.01		0.01	0.01		0.02***	0.02**
		(0.00)	(0.00)		(0.01)	(0.01)		(0.00)	(0.01)		(0.01)	(0.01)
cons	0.00	0.01	0.00	0.00	0.02***	0.02**	-0.03***	-0.01	-0.03**	-0.01	-0.01	-0.02
	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
R^2	0.17	0.21	0.22	0.26	0.13	0.28	0.39	0.38	0.34	0.28	0.31	0.33
N	392	525	294	392	525	294	392	525	294	392	525	294

Table 8: EU Countries (2nd Part), Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	GER			ITA			NLD			SWE		
	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Long Run Regression												
lnw	-1.27***	-0.97***	-1.18***	-1.02***	-0.71**	-1.05***	-1.13***	-1.01***	-1.16***	-0.68***	-0.86**	-0.70***
	(0.06)	(0.18)	(0.05)	(0.04)	(0.21)	(0.10)	(0.10)	(0.27)	(0.13)	(0.13)	(0.25)	(0.14)
lnY	1.08***	0.57***	1.07***	1.06***	0.56***	1.08***	0.86***	0.96***	0.88***	0.86***	0.78***	0.87***
	(0.05)	(0.10)	(0.04)	(0.05)	(0.09)	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)	(0.05)	(0.07)
RC	-0.24		-0.29	0.03		-0.04	0.08		0.06	-0.14		-0.03
	(0.29)		(0.32)	(0.07)		(0.10)	(0.14)		(0.17)	(0.09)		(0.10)
t^2	0.08	0.24	0.06	-0.24***	0.10	-0.17*	0.01	0.10	0.05	-0.40***	0.12	-0.30**
	(0.09)	(0.18)	(0.10)	(0.05)	(0.15)	(0.07)	(0.10)	(0.12)	(0.14)	(0.08)	(0.13)	(0.10)
epl		0.01	-0.03		0.01	0.01		0.01	0.01		0.00	0.00
		(0.01)	(0.02)		(0.01)	(0.02)		(0.01)	(0.02)		(0.00)	(0.00)
cons	-0.29	3.83**	-0.35	-0.98	2.54*	-1.24*	1.10	-0.41	1.00	-0.46	0.94	-0.62
	(0.53)	(1.10)	(0.49)	(0.49)	(1.07)	(0.46)	(0.62)	(0.94)	(0.65)	(0.63)	(1.18)	(0.67)
R^2	0.94	0.81	0.94	0.96	0.76	0.96	0.92	0.77	0.91	0.86	0.77	0.86
ECM												
Δlnw	-0.15	-0.24*	-0.16	-0.18**	-0.45**	-0.20**	-0.12	-0.27	-0.07	-0.04	-0.15	-0.04
	(0.09)	(0.10)	(0.12)	(0.05)	(0.14)	(0.05)	(0.08)	(0.18)	(0.08)	(0.06)	(0.09)	(0.08)
ΔlnY	0.21	0.35**	0.21	0.23**	0.46**	0.21*	0.14*	0.36*	0.13*	0.12	0.21	0.09
	(0.11)	(0.12)	(0.12)	(0.06)	(0.16)	(0.07)	(0.06)	(0.14)	(0.06)	(0.10)	(0.13)	(0.10)
ΔRC	0.03		0.01	0.01		-0.01	-0.09		-0.11	0.04		0.06*
	(0.14)		(0.13)	(0.07)		(0.07)	(0.14)		(0.16)	(0.03)		(0.03)
Δt^2	-0.29*	-0.07	-0.41*	0.23	0.04	0.62*	0.05	-0.32	-0.22	-0.13	-0.02	-0.05
	(0.10)	(0.32)	(0.16)	(0.11)	(0.24)	(0.23)	(0.11)	(0.19)	(0.15)	(0.16)	(0.15)	(0.25)
ϵ_{t-1}	-0.04*	-0.02	-0.03	-0.01	-0.03	-0.02	-0.01	-0.01	-0.01	-0.04	-0.02	-0.04
	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.03)
Δepl		0.00	-0.00		-0.00	-0.00		-0.01*	-0.01*		0.00	0.00
		(0.00)	(0.00)		(0.01)	(0.00)		(0.00)	(0.00)		(0.00)	(0.00)
cons	0.00	0.01	0.01	-0.02*	0.01	-0.03**	-0.01	0.03*	0.01	-0.01	0.00	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
R^2	0.18	0.35	0.24	0.08	0.28	0.08	0.09	0.11	0.08	0.09	0.11	0.08
N	392	525	294	392	525	294	392	525	294	392	525	294

Table 9: EU Countries (3rd Part), Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	FRA			UK		
	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$
Long Run Regression						
lnw	-0.97***	-0.68*	-1.00**	-0.99***	-0.82***	-0.94***
	(0.11)	(0.30)	(0.14)	(0.10)	(0.11)	(0.10)
lnY	1.04***	0.82***	1.06**	1.07***	0.93***	1.04***
	(0.06)	(0.03)	(0.07)	(0.04)	(0.05)	(0.04)
RC	-0.15		-0.21	-0.14		-0.16
	(0.17)		(0.24)	(0.25)		(0.32)
t^2	-0.06	-0.08	-0.20**	-0.13	-0.23*	-0.22*
	(0.04)	(0.08)	(0.04)	(0.10)	(0.10)	(0.10)
epl		0.02	0.05**		0.09	0.09*
		(0.02)	(0.01)		(0.05)	(0.03)
cons	-0.82**	0.17	-1.05**	-0.95*	-0.32	-0.83*
	(0.25)	(0.96)	(0.29)	(0.35)	(0.60)	(0.35)
R^2	0.95	0.90	0.95	0.95	0.88	0.95
ECM						
Δlnw	-0.22***	-0.36***	-0.20**	-0.31**	-0.13**	-0.32**
	(0.05)	(0.10)	(0.04)	(0.07)	(0.04)	(0.08)
ΔlnY	0.28***	0.32**	0.26**	0.44***	0.40***	0.49***
	(0.05)	(0.09)	(0.07)	(0.05)	(0.06)	(0.06)
ΔRC	-0.07		-0.11	-0.07		-0.11
	(0.04)		(0.06)	(0.19)		(0.22)
Δt^2	0.15	0.44***	0.39*	0.27*	0.21	0.38*
	(0.09)	(0.07)	(0.15)	(0.09)	(0.20)	(0.17)
ϵ_{t-1}	-0.04*	-0.01	-0.04*	-0.08***	0.01	-0.08***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
Δepl		0.00	0.00		0.03***	0.03
		(0.00)	(0.00)		(0.01)	(0.02)
cons	-0.01**	-0.01*	-0.03**	-0.03***	-0.02	-0.03***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
R^2	0.36	0.39	0.33	0.50	0.26	0.50
N	392	525	294	392	525	294

***, **,*: statistically significant at 1, 5, 10 % level, respectively: robust standard error in brackets.

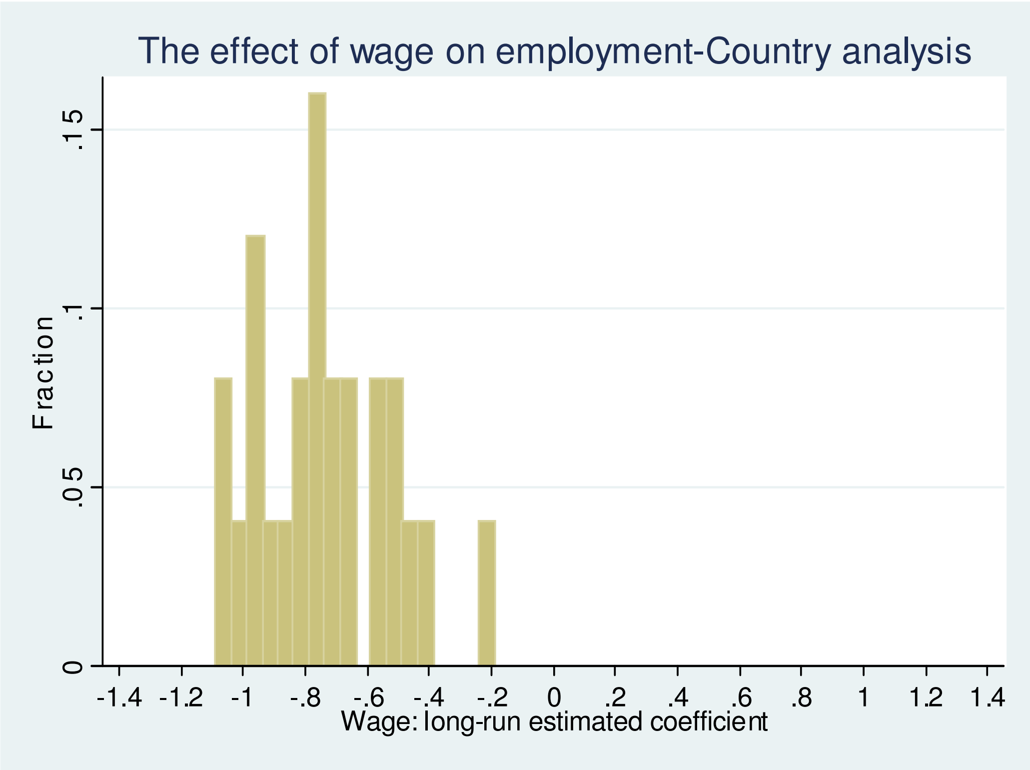

Figure 4: The effect of wage on employment.

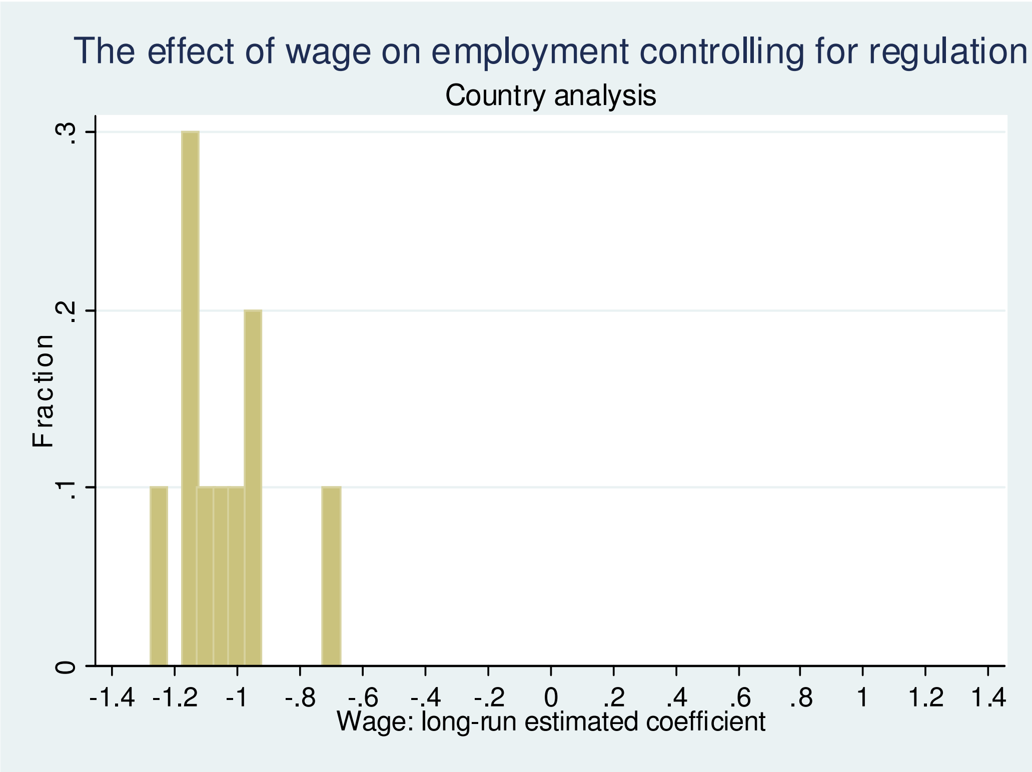

Figure 5: The effect of wage on employment.

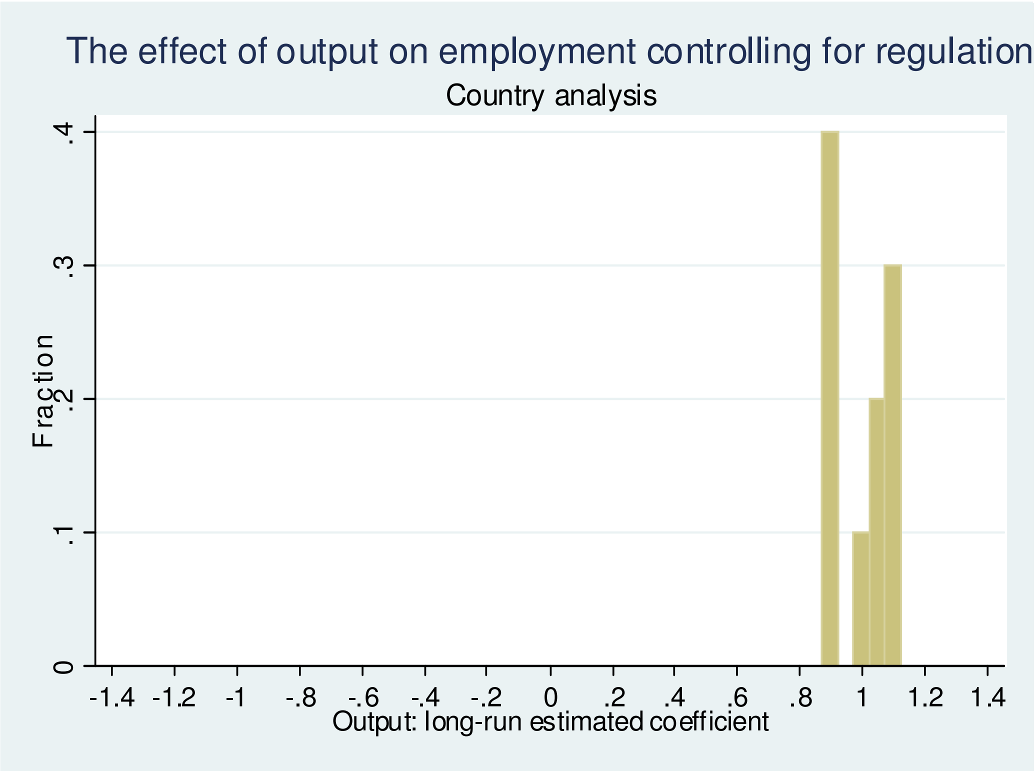

Figure 6: The effect of output on employment.

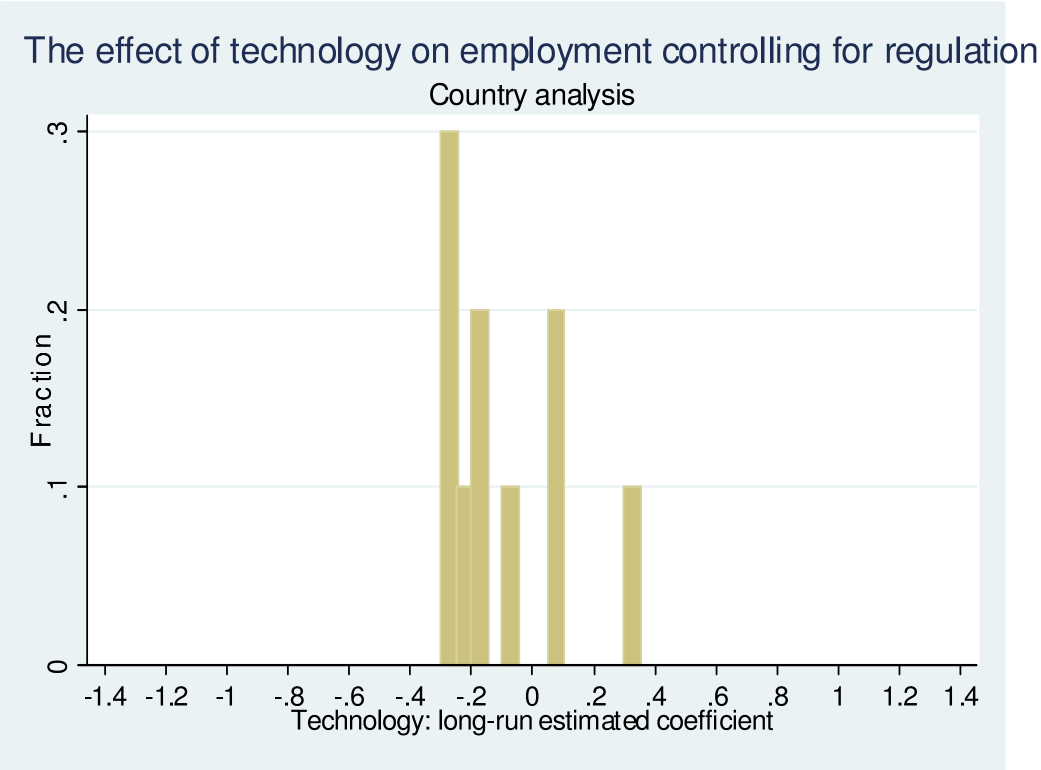

Figure 7: The effect of technology (t^2) on employment.

Table 10: EU Countries (1st Part), Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	AUT	DNK	FIN	FRA	GER
	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$
Long Run Regression					
$\ln w$	-1.09***	-1.17***	-1.00***	-1.05***	-1.18***
	(0.10)	(0.18)	(0.14)	(0.18)	(0.05)
$\ln Y$	1.09***	1.03***	1.06***	0.92***	1.09***
	(0.05)	(0.04)	(0.07)	(0.06)	(0.04)
RC	-0.39***	0.20*	-0.14	-0.14	0.10
	(0.09)	(0.08)	(0.12)	(0.11)	(0.17)
epl	0.04*	0.02	0.05***	-0.03	-0.04
	(0.02)	(0.02)	(0.01)	(0.03)	(0.02)
$t^2 * RC$	-0.00	-0.10***	-0.02	-0.05	-0.09*
	(0.00)	(0.02)	(0.04)	(0.04)	(0.04)
t^2	-0.03**	0.01	-0.02*	-0.01	0.03*
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
cons	-0.65	0.24	-1.12**	0.43	-0.58
	(0.51)	(0.87)	(0.35)	(0.31)	(0.50)
R^2	308	308	308	308	308
	0.96	0.97	0.95	0.93	0.94
ECM					
$\Delta \ln w$	-0.15*	-0.25**	-0.19***	-0.13*	-0.16
	(0.07)	(0.08)	(0.04)	(0.05)	(0.12)
$\Delta \ln Y$	0.12	0.23*	0.23**	0.26***	0.21
	(0.06)	(0.08)	(0.06)	(0.03)	(0.12)
ΔRC	-0.70***	-0.11	-0.43**	-0.21	-0.18
	(0.11)	(0.11)	(0.11)	(0.16)	(0.22)
Δepl	-0.02***	-0.01	0.00*	0.02**	0.00
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
Δt^2	-0.02	-0.05***	0.04**	0.02	-0.04*
	(0.02)	(0.01)	(0.01)	(0.03)	(0.01)
$\Delta\left(t^2 * RC\right)$	0.05**	-0.02	0.09**	0.03*	0.05
	(0.02)	(0.02)	(0.02)	(0.01)	(0.03)
$\hat{\epsilon}_{t-1}$	-0.01	-0.09***	-0.04*	-0.03	-0.03
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
cons	-0.01	0.02*	-0.04***	-0.03	0.00

Table 11: EU Countries (2nd Part), Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	ITA	NLD	SWE	UK
	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$
Long Run Regression				
$\ln w$	-0.99***	-1.15***	-0.69***	-0.93***
	(0.10)	(0.13)	(0.14)	(0.11)
$\ln Y$	1.12***	0.88***	0.87***	1.05***
	(0.05)	(0.06)	(0.07)	(0.04)
RC	0.36*	-0.02	-0.07	0.04
	(0.12)	(0.08)	(0.16)	(0.42)
epl	0.03	0.01	0.00	0.08*
	(0.02)	(0.02)	(0.00)	(0.03)
$t^2 * RC$	-1.14***	0.18	0.11	-0.51
	(0.26)	(0.27)	(0.51)	(0.48)
t^2	0.04	0.01	-0.32**	-0.15
	(0.08)	(0.12)	(0.09)	(0.09)
cons	-1.90***	1.04	-0.62	-1.01
	(0.41)	(0.66)	(0.67)	(0.48)
R^2	0.96	0.91	0.86	0.95
ECM				
$\Delta \ln w$	-0.20**	-0.06	-0.04	-0.32**
	(0.05)	(0.08)	(0.08)	(0.08)
$\Delta \ln Y$	0.21**	0.12*	0.09	0.47***
	(0.07)	(0.05)	(0.09)	(0.06)
ΔRC	-0.11	-0.45**	-0.17	-0.47
	(0.07)	(0.13)	(0.13)	(0.25)
Δepl	-0.00	-0.01*	0.00	0.03
	(0.00)	(0.00)	(0.00)	(0.02)
Δt^2	0.66**	-0.22	0.02	0.43*
	(0.22)	(0.15)	(0.30)	(0.19)
$\Delta\left(t^2 * RC\right)$	0.26	0.71***	0.54	1.08***
	(0.12)	(0.09)	(0.28)	(0.24)
$\hat{\epsilon}_{t-1}$	-0.03	-0.01	-0.04	-0.08***
	(0.02)	(0.01)	(0.02)	(0.01)
cons	-0.04**	-0.00	-0.02	-0.04***
	(0.01)	(0.01)	(0.01)	(0.01)

Table 12: Industry (1st Part), Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	food	textile	wood	pulp	coke	chemicals
	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$
Long Run Regression						
lnw	-0.92***	-0.94***	-0.93***	-0.97***	-0.51***	-0.87***
	(0.03)	(0.08)	(0.06)	(0.03)	(0.11)	(0.17)
lnY	1.03***	0.98***	0.98***	1.09***	0.77***	1.06***
	(0.05)	(0.04)	(0.07)	(0.05)	(0.05)	(0.10)
t^2	-0.16*	-0.16**	-0.13	-0.32*	-0.23	-0.77
	(0.06)	(0.05)	(0.08)	(0.11)	(0.16)	(0.45)
cons	-1.04*	-0.30	-0.49	-1.24**	-1.13***	-1.50
	(0.39)	(0.51)	(0.49)	(0.34)	(0.21)	(0.81)
N	490.00	490.00	490.00	490.00	457.00	490.00
R^2	0.97	0.96	0.91	0.95	0.87	0.75
ECM						
Δlnw	-0.28***	-0.51***	-0.23***	-0.12**	-0.03*	-0.19***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.01)	(0.03)
ΔlnY	0.27***	0.61***	0.30***	0.20***	0.05*	0.12*
	(0.03)	(0.03)	(0.02)	(0.04)	(0.02)	(0.01)
Δt^2	-0.10	-0.15	0.03	-0.24*	-0.34	-0.01
	(0.07)	(0.11)	(0.09)	(0.10)	(0.20)	(0.07)
ϵ_{t-1}	-0.02**	-0.03*	-0.02*	-0.02*	-0.02	-0.02***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
cons	-0.00	-0.01*	-0.01*	0.00	-0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
R^2	0.26	0.65	0.34	0.22	0.05	0.30
N	490	490	490	490	457	490

***, **,*: statistically significant at 1, 5, 10 % level, respectively: robust standard error in brackets.

Table 13: Industry (2nd Part), Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	rubber	othernonmetal	basicmetal	machinery	electrical	transporteq
	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$
Long Run Regression						
lnw	-0.87***	-0.91***	-0.94***	-0.97***	-0.92***	-1.03***
	(0.07)	(0.03)	(0.05)	(0.02)	(0.03)	(0.03)
lnY	1.01***	1.05***	1.01***	1.01***	1.03***	0.99***
	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)
t^2	-0.07	-0.18***	-0.06	-0.08**	-0.42*	-0.11
	(0.08)	(0.04)	(0.04)	(0.02)	(0.16)	(0.06)
cons	-0.93*	-1.12***	-0.67***	-0.47**	-0.73*	-0.01
	(0.34)	(0.21)	(0.14)	(0.13)	(0.28)	(0.12)
R^2	0.97	0.99	0.98	0.99	0.96	0.99
ECM						
Δlnw	-0.34***	-0.36***	-0.28***	-0.44***	-0.19	-0.26***
	(0.06)	(0.05)	(0.04)	(0.03)	(0.12)	(0.05)
ΔlnY	0.39***	0.42***	0.34***	0.46***	0.16	0.28***
	(0.06)	(0.04)	(0.03)	(0.03)	(0.12)	(0.03)
Δt^2	0.00	0.00	0.04	-0.09	-0.25	-0.16
	(0.08)	(0.07)	(0.10)	(0.07)	(0.12)	(0.12)
ϵ_{t-1}	-0.03**	-0.07***	-0.06*	-0.09***	-0.06**	-0.09***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
cons	0.00	-0.01*	-0.01	0.00	0.01	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
R^2	0.34	0.44	0.41	0.52	0.22	0.37
N	490	490	490	490	490	490

***, **,*: statistically significant at 1, 5, 10 % level, respectively: robust standard error in brackets.

Table 14: Industry (3rd Part), Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	manufacturing	sale	wholesale	retail	transport	post
	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$
Long Run Regression						
lnw	-0.86***	-0.94***	-0.89***	-0.82***	-1.02***	-0.88***
	(0.10)	(0.07)	(0.09)	(0.12)	(0.05)	(0.04)
lnY	0.95***	1.09***	1.05***	1.02***	1.04***	1.02***
	(0.07)	(0.10)	(0.10)	(0.14)	(0.05)	(0.04)
t^2	-0.03	-0.00	-0.08	0.01	-0.17**	-0.44***
	(0.09)	(0.07)	(0.06)	(0.09)	(0.05)	(0.07)
cons	-0.48	-1.71*	-1.45	-1.41	-0.78*	-0.97**
	(0.60)	(0.67)	(0.73)	(1.35)	(0.32)	(0.26)
R^2	0.90	0.91	0.92	0.78	0.97	0.97
ECM						
Δlnw	-0.46***	-0.31**	-0.36***	-0.38***	-0.31**	-0.14**
	(0.07)	(0.08)	(0.06)	(0.04)	(0.08)	(0.03)
ΔlnY	0.45***	0.29*	0.38***	0.34***	0.24**	0.25***
	(0.07)	(0.10)	(0.06)	(0.07)	(0.06)	(0.05)
Δt^2	-0.22**	0.23	-0.05	0.13	0.01	-0.29*
	(0.07)	(0.11)	(0.08)	(0.06)	(0.08)	(0.11)
ϵ_{t-1}	-0.01**	-0.02**	-0.02**	-0.01***	-0.01	-0.01
	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)
cons	0.01*	-0.00	0.01*	0.01*	0.01	0.01
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
R^2	0.48	0.28	0.34	0.36	0.24	0.13
N	490	490	490	490	490	490

***, **,*: statistically significant at 1, 5, 10 % level, respectively: robust standard error in brackets.

Table 15: Industry (4th Part), Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	agriculture	mining	electricity	construction	hotels	financial
	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$
Long Run Regression						
lnw	-0.97***	-1.09***	-1.12***	-0.82***	-0.75***	-1.07***
	(0.09)	(0.23)	(0.07)	(0.06)	(0.11)	(0.07)
lnY	1.28***	0.69***	0.96***	0.96***	0.97***	1.05***
	(0.10)	(0.15)	(0.06)	(0.05)	(0.08)	(0.03)
t^2	0.10	-0.26	-0.12	-0.12***	0.01	-0.12
	(0.09)	(0.42)	(0.13)	(0.02)	(0.07)	(0.08)
cons	-4.46***	1.44	-0.19	-0.60	-1.26	-0.76
	(0.86)	(1.02)	(0.46)	(0.54)	(0.96)	(0.37)
R^2	0.88	0.59	0.93	0.96	0.82	0.97
ECM						
Δlnw	-0.50*	-0.10**	-0.17**	-0.63***	-0.49***	-0.16
	(0.19)	(0.03)	(0.05)	(0.07)	(0.08)	(0.07)
ΔlnY	0.30*	0.01	0.09*	0.69***	0.43***	0.20**
	(0.12)	(0.09)	(0.04)	(0.06)	(0.10)	(0.06)
Δt^2	0.61***	0.09	-0.53***	0.12	0.19	-0.59***
	(0.10)	(0.23)	(0.12)	(0.09)	(0.09)	(0.08)
ϵ_{t-1}	-0.02	-0.02**	-0.01	-0.01**	-0.01*	-0.03*
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)
cons	-0.02**	-0.03**	0.02**	-0.01	0.01	0.04***
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
R^2	0.46	0.11	0.19	0.65	0.47	0.25
N	490	490	490	490	490	490

***, **,*: statistically significant at 1, 5, 10 % level, respectively: robust standard error in brackets.

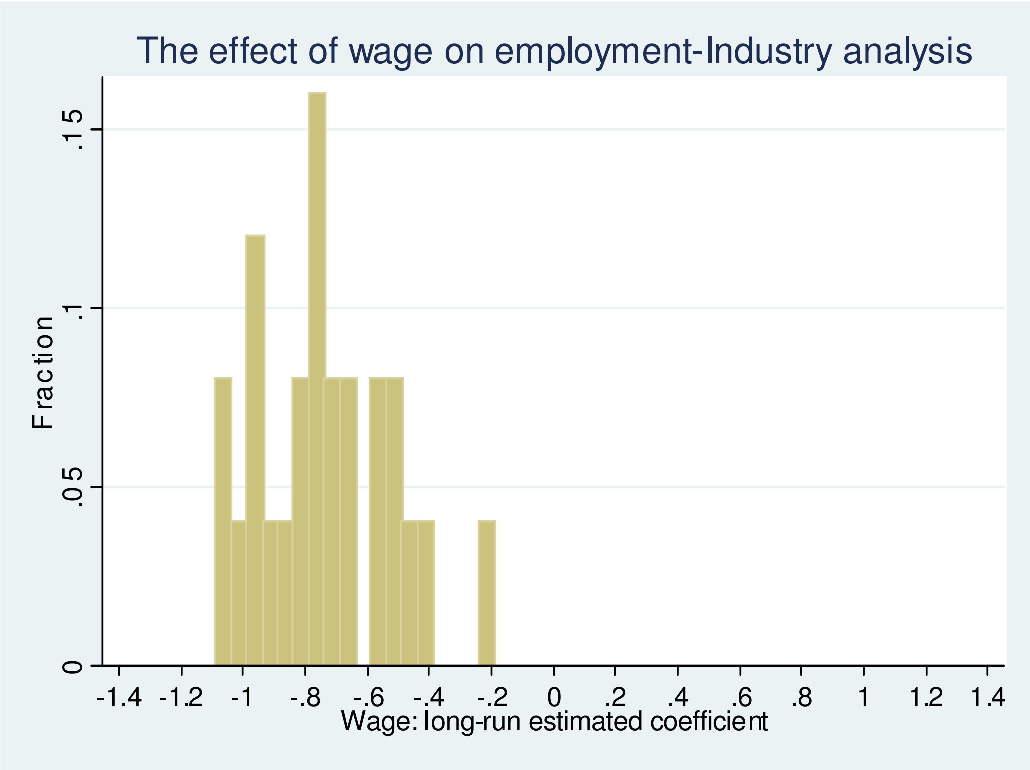

Figure 8: The effect of wage on employment.

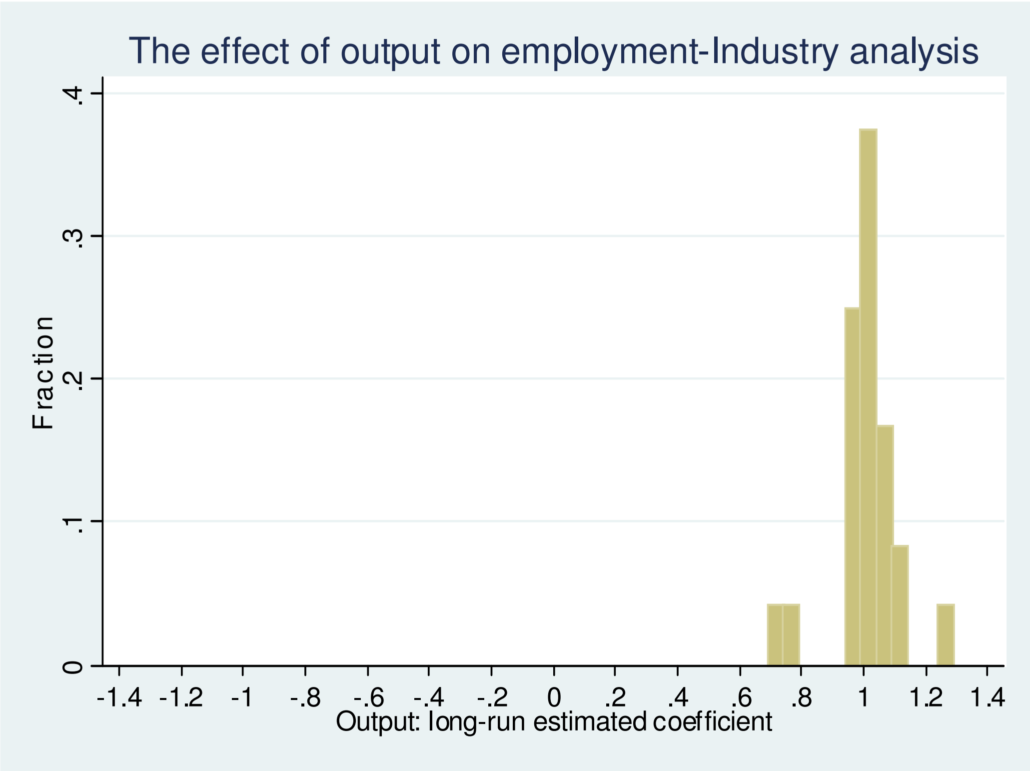

Figure 9: The effect of output on employment.

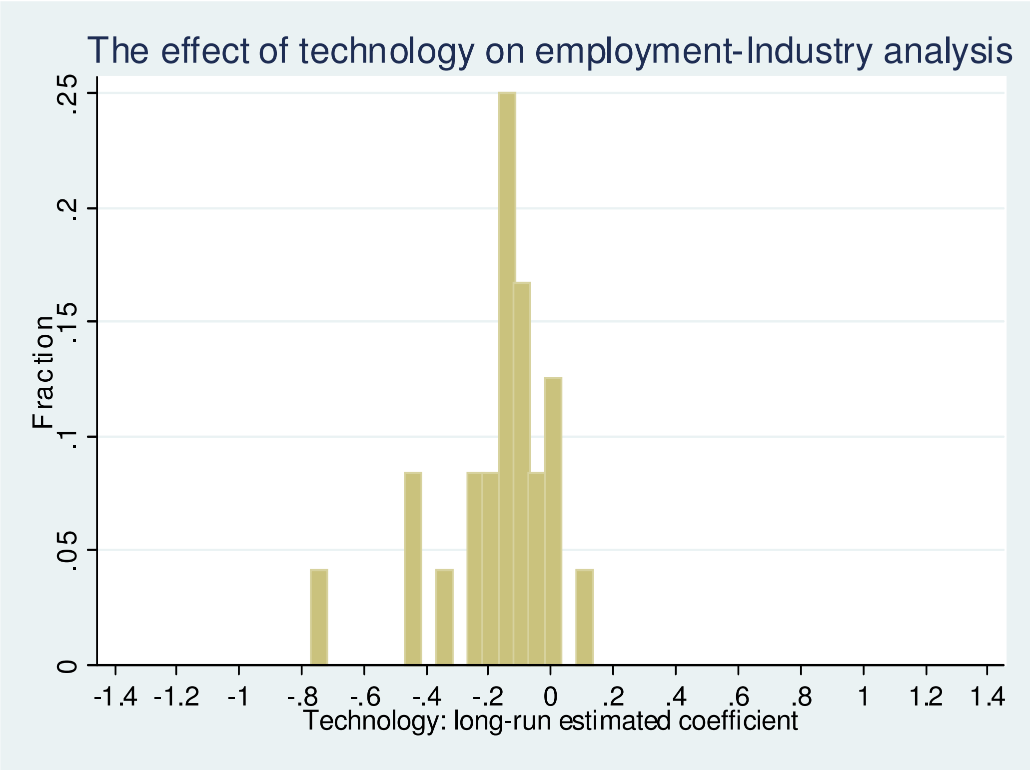

Figure 10: The effect of technology (t^2) on employment.

Table 16: Industry (5th Part), Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	food			text			wood		
	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Long Run Regression									
lnw	-0.92***	-0.89***	-0.91***	-0.96***	-0.90***	-0.91***	-0.94***	-0.88***	-0.90***
	(0.03)	(0.03)	(0.02)	(0.05)	(0.05)	(0.05)	(0.05)	(0.07)	(0.07)
lnY	1.04***	0.94***	0.97***	1.03***	0.93***	0.99***	1.02***	0.89***	0.94***
	(0.05)	(0.04)	(0.05)	(0.03)	(0.02)	(0.04)	(0.06)	(0.11)	(0.12)
epl	0.00		-0.03	-0.09**		-0.05	-0.06		-0.03
	(0.02)		(0.02)	(0.03)		(0.02)	(0.04)		(0.03)
t^2	-0.11	-0.16	-0.10	-0.10	-0.28**	-0.17	-0.08	-0.17	-0.14
	(0.06)	(0.09)	(0.09)	(0.06)	(0.08)	(0.11)	(0.04)	(0.09)	(0.09)
RC		-1.43	-0.83		-1.74	-0.72		-1.40	-1.33
		(1.31)	(1.17)		(1.37)	(1.20)		(1.55)	(1.55)
cons	-1.17**	-0.06	-0.36	-0.47	0.25	-0.27	-0.61	0.28	0.02
	(0.39)	(0.51)	(0.50)	(0.32)	(0.49)	(0.61)	(0.36)	(0.84)	(0.93)
R^2	0.97	0.99	0.99	0.98	0.99	0.99	0.95	0.95	0.96
ECM									
Δlnw	-0.27***	-0.18***	-0.22***	-0.50***	-0.51***	-0.53***	-0.23***	-0.24***	-0.26***
	(0.05)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.04)	(0.04)	(0.05)
ΔlnY	0.23***	0.18**	0.19*	0.65***	0.63***	0.65***	0.27***	0.29***	0.26***
	(0.03)	(0.05)	(0.06)	(0.04)	(0.07)	(0.07)	(0.03)	(0.03)	(0.04)
Δepl	-0.00		0.00	-0.01		-0.01	-0.01		-0.00
	(0.00)		(0.00)	(0.00)		(0.00)	(0.00)		(0.00)
Δt^2	0.04	-0.00	0.08	-0.00	0.10	0.03	0.26	0.20	0.21
	(0.11)	(0.11)	(0.17)	(0.21)	(0.30)	(0.34)	(0.23)	(0.16)	(0.29)
ϵ_{t-1}	-0.03*	-0.03	-0.03	-0.07***	-0.04*	-0.08**	-0.06*	-0.06	-0.09
	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)	(0.04)
ΔRC		-0.10	0.11		0.35	0.64		-0.47*	-0.48
		(0.48)	(0.50)		(0.42)	(0.50)		(0.17)	(0.33)
cons	-0.01	-0.01	-0.01	-0.02	-0.02*	-0.02	-0.02	-0.02*	-0.02
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
R^2	0.26	0.15	0.18	0.63	0.61	0.63	0.31	0.38	0.37
N	322	280	210	322	280	210	322	280	210

***, **,*: statistically significant at 1, 5, 10 % level, respectively: robust standard error in brackets.

Table 17: Industry (6th Part), Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	coke			pulp			chemicals		
	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Long Run Regression									
lnw	-0.98***	-0.96***	-0.97***	-0.58***	-0.54**	-0.62***	-0.84**	-1.08***	-1.11***
	(0.05)	(0.03)	(0.03)	(0.10)	(0.15)	(0.12)	(0.21)	(0.06)	(0.07)
lnY	1.09***	1.02***	1.05***	0.83***	0.77***	0.86***	0.96***	1.07***	1.07***
	(0.05)	(0.03)	(0.04)	(0.06)	(0.08)	(0.09)	(0.14)	(0.04)	(0.05)
epl	0.01		-0.02	-0.05		-0.08	0.17		0.01
	(0.03)		(0.01)	(0.05)		(0.05)	(0.10)		(0.02)
t^2	-0.31*	-0.27*	-0.21	-0.35	0.07	-0.00	-0.65	-0.18	-0.10
	(0.14)	(0.09)	(0.09)	(0.17)	(0.20)	(0.25)	(0.42)	(0.10)	(0.10)
RC		0.13	0.70		2.77	2.35		0.24	0.15
		(0.64)	(0.83)		(1.85)	(1.60)		(1.45)	(1.53)
cons	-1.29**	-0.70*	-0.99*	-1.04***	-1.56**	-1.57**	-1.19	-0.87	-0.79
	(0.37)	(0.28)	(0.37)	(0.20)	(0.40)	(0.36)	(0.60)	(0.50)	(0.54)
R^2	0.93	0.98	0.97	0.89	0.88	0.89	0.73	0.98	0.98
ECM									
Δlnw	-0.13*	-0.09**	-0.13**	-0.00	-0.02	0.01	-0.18**	-0.19**	-0.19*
	(0.05)	(0.03)	(0.03)	(0.02)	(0.01)	(0.01)	(0.06)	(0.05)	(0.06)
ΔlnY	0.19***	0.18*	0.17	0.03	0.03	0.01	0.13***	0.16*	0.15*
	(0.03)	(0.06)	(0.08)	(0.02)	(0.02)	(0.02)	(0.02)	(0.05)	(0.05)
Δepl	-0.00		-0.01	-0.00		0.00	-0.00		-0.00
	(0.01)		(0.00)	(0.01)		(0.01)	(0.01)		(0.01)
Δt^2	-0.28*	-0.22	-0.28	0.21	-0.30	0.13	0.28	0.14	0.27
	(0.12)	(0.22)	(0.22)	(0.51)	(0.27)	(0.65)	(0.14)	(0.12)	(0.14)
ϵ_{t-1}	-0.02	-0.06***	-0.06**	-0.02	-0.03	-0.02	-0.02***	-0.04	-0.04
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.02)	(0.00)	(0.02)	(0.03)
ΔRC		-0.27	-0.18		1.31	1.29		0.69	0.73
		(0.69)	(0.67)		(2.35)	(2.17)		(0.50)	(0.53)
cons	0.00	-0.00	0.00	-0.03	-0.00	-0.03	-0.01	-0.01	-0.02*
	(0.01)	(0.01)	(0.01)	(0.03)	(0.01)	(0.03)	(0.01)	(0.01)	(0.01)
R^2	0.23	0.19	0.20	0.03	0.06	0.03	0.30	0.19	0.18
N	336	290	220	314	290	220	336	290	220

***, **,*: statistically significant at 1, 5, 10 % level, respectively; robust standard error in brackets

Table 18: Industry (7th Part), Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	text			wood		
	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$
	(1)	(2)	(3)	(1)	(2)	(3)
Long Run Regression						
lnw	-0.96***	-0.90***	-0.91***	-0.94***	-0.88** *	-0.90***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.07)	(0.07)
lnY	1.03***	0.93***	0.99***	1.02***	0.89***	0.94***
	(0.03)	(0.02)	(0.04)	(0.06)	(0.11)	(0.12)
epl	-0.09**		-0.05	-0.06		-0.03
	(0.03)		(0.02)	(0.04)		(0.03)
t^2	-0.10	-0.28**	-0.17	-0.08	-0.17	-0.14
	(0.06)	(0.08)	(0.11)	(0.04)	(0.09)	(0.09)
RC		-1.74	-0.72		-1.40	-1.33
		(1.37)	(1.20)		(1.55)	(1.55)
cons	-0.47	0.25	-0.27	-0.61	0.28	0.02
	(0.32)	(0.49)	(0.61)	(0.36)	(0.84)	(0.93)
R^2	0.98	0.99	0.99	0.95	0.95	0.96
ECM						
Δlnw	-0.50***	-0.51***	-0.53***	-0.23***	-0.24***	-0.26***
	(0.04)	(0.05)	(0.05)	(0.04)	(0.04)	(0.05)
ΔlnY	0.65***	0.63***	0.65***	0.27***	0.29***	0.26***
	(0.04)	(0.07)	(0.07)	(0.03)	(0.03)	(0.04)
Δepl	-0.01		-0.01	-0.01		-0.00
	(0.00)		(0.00)	(0.00)		(0.00)
Δt^2	-0.00	0.10	0.03	0.26	0.20	0.21
	(0.21)	(0.30)	(0.34)	(0.23)	(0.16)	(0.29)
ϵ_{t-1}	-0.07***	-0.04*	-0.08**	-0.06*	-0.06	-0.09
	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)	(0.04)
ΔRC		0.35	0.64		-0.47*	-0.48
		(0.42)	(0.50)		(0.17)	(0.33)
cons	-0.02	-0.02*	-0.02	-0.02	-0.02*	-0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
R^2	0.63	0.61	0.63	0.31	0.38	0.37
N	322	280	210.00	322.00	280.00	210.00

***, **,*: statistically significant at 1, 5, 10 % level, respectively; robust standard error in brackets.

Table 19: Industry (8th Part), Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	rubber			othernometall			basicmetall		
	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Long Run Regression									
lnw	-0.92***	-0.94***	-0.96***	-0.91***	-0.91***	-0.93***	-0.96***	-0.94***	-0.97***
	(0.04)	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)	(0.05)	(0.04)	(0.03)
lnY	1.03***	0.98***	1.01***	1.05***	1.00***	1.04***	1.03***	1.04***	1.12***
	(0.02)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)
epl	-0.03		-0.02	0.00		-0.02*	-0.02		-0.06*
	(0.01)		(0.01)	(0.02)		(0.01)	(0.02)		(0.02)
t^2	-0.00	-0.17	-0.10	-0.09*	-0.25**	-0.12	-0.02	0.03	0.13
	(0.07)	(0.08)	(0.07)	(0.04)	(0.06)	(0.05)	(0.05)	(0.13)	(0.12)
RC		-0.90	-0.29		-1.37	-0.36		2.22	3.10
		(1.01)	(0.74)		(0.88)	(0.74)		(1.94)	(1.38)
cons	-0.90**	-0.22	-0.51	-1.16***	-0.43	-0.86*	-0.72**	-1.33	-2.06**
	(0.26)	(0.36)	(0.29)	(0.22)	(0.41)	(0.37)	(0.19)	(0.72)	(0.59)
R^2	0.98	0.99	0.99	0.99	0.99	0.99	0.98	0.98	0.98
ECM									
Δlnw	-0.34***	-0.34***	-0.38***	-0.43***	-0.43***	-0.45***	-0.29***	-0.25***	-0.28**
	(0.07)	(0.06)	(0.06)	(0.03)	(0.06)	(0.02)	(0.04)	(0.04)	(0.06)
ΔlnY	0.42***	0.43***	0.44***	0.41***	0.43***	0.43***	0.29***	0.31***	0.31***
	(0.06)	(0.07)	(0.08)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.05)
Δepl	-0.00		0.00	-0.00		0.00	0.00		0.00
	(0.00)		(0.00)	(0.01)		(0.01)	(0.01)		(0.01)
dt^2	0.06	0.22	0.20	0.31	0.13	0.25	0.52*	0.34	0.72
	(0.21)	(0.20)	(0.33)	(0.21)	(0.12)	(0.17)	(0.22)	(0.20)	(0.34)
L.error1	-0.05	-0.08***	-0.14***	-0.09**	-0.13**	-0.06*	-0.08***	-0.22**	-0.09**
	(0.03)	(0.01)	(0.01)	(0.02)	(0.03)	(0.02)	(0.02)	(0.05)	(0.02)
dRC		0.34	0.86		-1.22	-0.92		-0.60	-0.01
		(1.13)	(1.16)		(0.83)	(0.78)		(0.89)	(0.87)
cons	-0.00	-0.01	-0.01	-0.02	-0.02**	-0.02**	-0.03*	-0.02*	-0.04*
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
R^2	0.34	0.42	0.47	0.49	0.55	0.63	0.45	0.43	0.48
N	322	280	210	322	280	210	322	280	210

Table 20: Industry (9th Part), Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	machinery			electrical			manufacturing		
	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Long Run Regression									
lnw	-0.99***	-0.97***	-1.00***	-0.93***	-0.92***	-0.93***	-0.89***	-0.82***	-0.84***
	(0.02)	(0.03)	(0.01)	(0.04)	(0.02)	(0.02)	(0.10)	(0.10)	(0.10)
lnY	1.02***	1.02***	1.06***	1.03***	1.02***	1.08***	1.00***	0.87***	0.91***
	(0.02)	(0.02)	(0.01)	(0.04)	(0.03)	(0.04)	(0.06)	(0.10)	(0.11)
epl	-0.01		-0.04*	0.02		-0.03	-0.08		-0.02
	(0.01)		(0.01)	(0.03)		(0.03)	(0.04)		(0.03)
t^2	-0.06**	-0.07	-0.03	-0.42*	-0.34	-0.33	-0.06	-0.18	-0.16
	(0.02)	(0.05)	(0.04)	(0.17)	(0.21)	(0.25)	(0.08)	(0.13)	(0.14)
RC		0.42	0.91		0.19	0.64		-2.16	-1.67
		(0.81)	(0.46)		(1.13)	(1.29)		(2.63)	(2.68)
cons	-0.49**	-0.62*	-0.86***	-0.81*	-0.74*	-1.15**	-0.49	0.54	0.21
	(0.13)	(0.24)	(0.16)	(0.28)	(0.26)	(0.30)	(0.47)	(1.02)	(1.07)
R^2	0.99	0.99	0.99	0.95	0.97	0.96	0.93	0.94	0.95
ECM									
Δlnw	-0.48***	-0.47***	-0.49***	-0.18	-0.12	-0.13	-0.44***	-0.31*	-0.30
	(0.04)	(0.05)	(0.07)	(0.13)	(0.12)	(0.13)	(0.08)	(0.11)	(0.14)
ΔlnY	0.44***	0.45***	0.46***	0.14	0.14	0.14	0.42***	0.35**	0.33**
	(0.03)	(0.03)	(0.04)	(0.12)	(0.10)	(0.11)	(0.08)	(0.10)	(0.10)
Δepl	-0.00		-0.00	0.00		0.00	-0.01		-0.01*
	(0.00)		(0.00)	(0.01)		(0.01)	(0.00)		(0.00)
Δt^2	0.14	0.01	0.22	-0.40	-0.34	-0.54	-0.10	-0.06	-0.10
	(0.17)	(0.12)	(0.21)	(0.27)	(0.31)	(0.51)	(0.18)	(0.20)	(0.31)
ϵ_{t-1}	-0.12***	-0.11**	-0.16**	-0.07**	-0.08	-0.02	-0.03**	-0.07	-0.01
	(0.03)	(0.03)	(0.04)	(0.02)	(0.04)	(0.01)	(0.01)	(0.04)	(0.01)
ΔRC		-0.15	0.32		-2.14	-1.83		-0.52	-0.39
		(0.87)	(1.02)		(1.31)	(1.37)		(0.90)	(0.97)
cons	-0.01	-0.00	-0.01	0.02	0.00	0.02	-0.00	-0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
R^2	0.56	0.56	0.61	0.21	0.22	0.23	0.48	0.33	0.33
N	322	280	210	322	280	210	322	280	210

***, **,*: statistically significant at 1, 5, 10 % level, respectively: robust standard error in brackets.

Table 21: Industry (10th Part), Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	transport			post			machinery		
	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Long Run Regression									
lnw	-1.02***	-1.05***	-1.08***	-0.88***	-0.89***	-0.89***	-0.99***	-0.97***	-1.00***
	(0.05)	(0.05)	(0.04)	(0.04)	(0.02)	(0.02)	(0.02)	(0.03)	(0.01)
lnY	1.06***	1.13***	1.22***	1.03***	1.02***	1.05***	1.02***	1.02***	1.06***
	(0.05)	(0.07)	(0.07)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)
epl	-0.03		-0.07*	-0.02		-0.02	-0.01		-0.04*
	(0.02)		(0.02)	(0.02)		(0.02)	(0.01)		(0.01)
t^2	-0.17*	-0.15	-0.06	-0.43***	-0.77***	-0.75***	-0.06**	-0.07	-0.03
	(0.06)	(0.18)	(0.13)	(0.09)	(0.12)	(0.15)	(0.02)	(0.05)	(0.04)
RC		0.16	0.40		-0.82*	-0.72*		0.42	0.91
		(0.34)	(0.27)		(0.34)	(0.31)		(0.81)	(0.46)
cons	-0.82*	-1.67*	-2.43*	-1.04***	-0.39*	-0.62	-0.49**	-0.62*	-0.86***
	(0.33)	(0.69)	(0.75)	(0.20)	(0.16)	(0.27)	(0.13)	(0.24)	(0.16)
R^2	0.96	0.97	0.97	0.97	0.98	0.97	0.99	0.99	0.99
ECM									
Δlnw	-0.31**	-0.23***	-0.24***	-0.12*	-0.13	-0.14	-0.48***	-0.47***	-0.49***
	(0.10)	(0.05)	(0.05)	(0.04)	(0.07)	(0.09)	(0.04)	(0.05)	(0.07)
ΔlnY	0.18*	0.25*	0.25*	0.24**	0.36**	0.36**	0.44***	0.45***	0.46***
	(0.07)	(0.08)	(0.10)	(0.07)	(0.08)	(0.09)	(0.03)	(0.03)	(0.04)
Δepl	0.00		-0.00	0.01		0.01	-0.00		-0.00
	(0.01)		(0.01)	(0.01)		(0.01)	(0.00)		(0.00)
Δt^2	0.38*	0.24	0.46*	-0.08	-0.45	-0.46	0.14	0.01	0.22
	(0.15)	(0.11)	(0.17)	(0.18)	(0.24)	(0.31)	(0.17)	(0.12)	(0.21)
ϵ_{t-1}	-0.01	-0.02	-0.02	-0.02	-0.02	-0.11**	-0.12***	-0.03	-0.16**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.03)	(0.03)	(0.02)	(0.04)
ΔRC		0.05	0.04		0.06	0.06		-0.15	0.32
		(0.04)	(0.04)		(0.07)	(0.07)		(0.87)	(1.02)
cons	-0.01	-0.00	-0.02	-0.01	0.01	0.01	-0.01	-0.00	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N	322	280	210	322	280	210	322	280	210
R^2	0.26	0.23	0.25	0.12	0.20	0.21	0.56	0.56	0.61

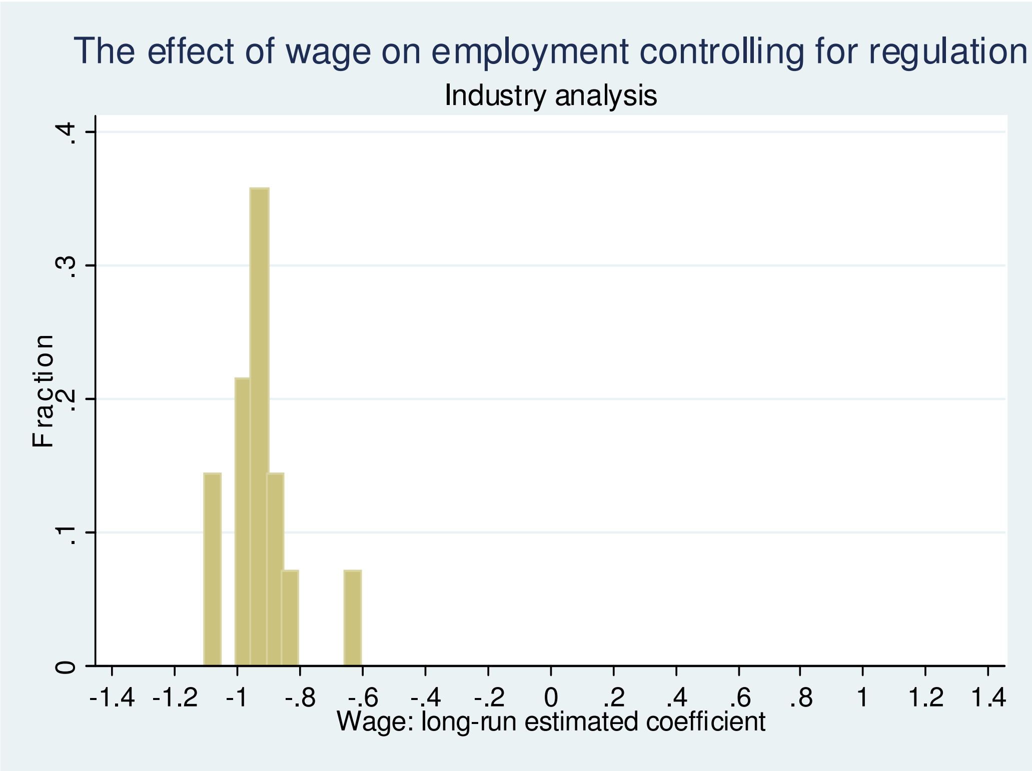

Figure 11: The effect of wage on employment.

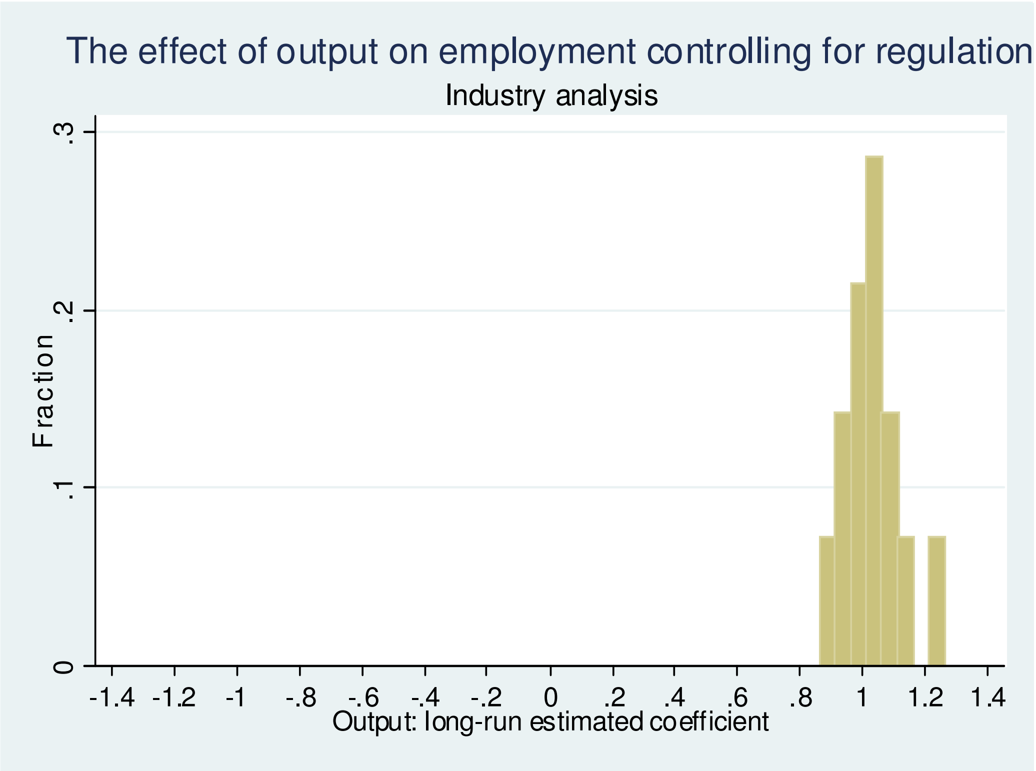

Figure 12: The effect of output on employment.

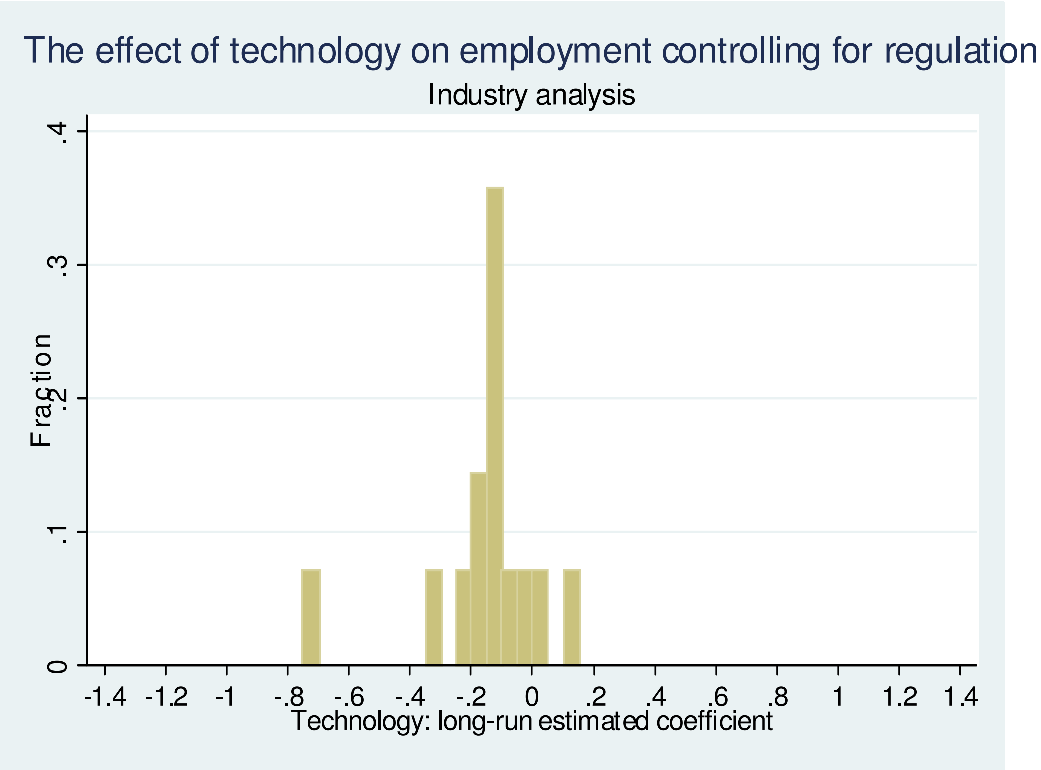

Figure 13: The effect of technology (t^2) on employment.

Table 22: Non-EU Countries and EU Aggregates, Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	AUS	JPN	KOR	USA
	β/s.e.	β/s.e.	β/s.e.	β/s.e.
Long Run Regression				
lnw	-0.92*	-0.83*	-0.78***	-0.92***
	(0.36)	(0.31)	(0.20)	(0.19)
lnY	0.74***	0.91***	0.82***	0.76***
	(0.05)	(0.15)	(0.16)	(0.07)
$\frac{I_{ICT}}{Y}$	0.88	-1.65	0.68	1.09
	(1.04)	(1.82)	(1.72)	(1.31)
cons	1.46	-0.82	-0.08	2.02*
	(0.93)	(2.16)	(1.38)	(0.93)
N	850	775	700	850
R^2	0.77	0.70	0.67	0.83
ECM				
Δlnw	-0.44***	-0.03	-0.52***	-0.28***
	(0.07)	(0.03)	(0.08)	(0.07)
ΔlnY	0.44***	0.12*	0.69***	0.41***
	(0.11)	(0.05)	(0.07)	(0.05)
$\Delta \frac{I_{ICT}}{Y}$	0.32**	0.53	0.36*	0.42**
	(0.09)	(0.46)	(0.14)	(0.12)
ϵ_{t-1}	-0.01	-0.01	-0.01	-0.02
	(0.01)	(0.01)	(0.02)	(0.01)
cons	0.01	0.01	0.01	0.01
	(0.01)	(0.00)	(0.01)	(0.00)
N	825	750	650	825
R^2	0.41	0.10	0.58	0.32

***, **,*: statistically significant at 1, 5, 10 % level, respectively: robust standard error in brackets.

Table 23: EU 15 Countries (first part), Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	AUT	DNK	FIN	GER
	β/s.e.	β/s.e.	β/s.e.	β/s.e.
Long Run Regression				
lnw	-0.53	-0.59**	-0.64*	-0.84***
	(0.39)	(0.20)	(0.29)	(0.20)
lnY	0.79***	0.74***	0.70***	0.62***
	(0.10)	(0.11)	(0.10)	(0.09)
$\frac{I_{ICT}}{Y}$	-0.53	0.12	-0.91	-0.48
	(0.50)	(1.12)	(1.54)	(2.56)
cons	-0.44	-0.17	0.61	3.08*
	(1.52)	(1.31)	(0.56)	(1.12)
N	725	850	850	350
R^2	0.72	0.73	0.65	0.86
ECM				
Δlnw	-0.21**	-0.16***	-0.24***	-0.30*
	(0.07)	(0.04)	(0.06)	(0.11)
ΔlnY	0.19**	0.25***	0.41***	0.40***
	(0.06)	(0.05)	(0.07)	(0.09)
$\Delta\frac{I_{ICT}}{Y}$	0.61*	0.25	0.40	1.82***
	(0.24)	(0.14)	(0.20)	(0.41)
ϵ_{t-1}	-0.00	-0.01	-0.01	-0.03
	(0.01)	(0.01)	(0.01)	(0.02)
cons	0.00	0.00	-0.00	-0.01
	(0.00)	(0.01)	(0.01)	(0.01)
N	675	825	825	300
R^2	0.19	0.18	0.32	0.39

***, **,*: statistically significant at 1, 5, 10 % level, respectively: robust standard error in brackets.

Table 24: EU 15 Countries (second part), Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	ITA	NLD	SWE	UK
	β/s.e.	β/s.e.	β/s.e.	β/s.e.
Long Run Regression				
lnw	-0.86***	-1.09**	-0.78***	-0.83***
	(0.14)	(0.32)	(0.11)	(0.10)
lnY	0.55***	0.96***	0.83***	0.91***
	(0.08)	(0.06)	(0.05)	(0.04)
$\frac{I_{ICT}}{Y}$	3.99*	1.21	0.30	-0.05
	(1.66)	(1.72)	(1.52)	(0.46)
cons	3.16**	-0.09	-0.04	-0.06
	(0.92)	(0.88)	(0.76)	(0.47)
N	850	850	300	850
R^2	0.75	0.72	0.85	0.87
ECM				
Δlnw	-0.29*	-0.33	-0.03	-0.14**
	(0.11)	(0.20)	(0.07)	(0.04)
ΔlnY	0.31**	0.27	-0.10	0.35***
	(0.10)	(0.19)	(0.11)	(0.05)
$\Delta \frac{I_{ICT}}{Y}$	0.29	0.33	0.59	0.25
	(0.30)	(0.17)	(0.31)	(0.20)
ϵ_{t-1}	-0.02	-0.01	-0.01	0.00
	(0.01)	(0.00)	(0.01)	(0.02)
cons	0.01*	0.01	0.01	-0.01
	(0.00)	(0.00)	(0.01)	(0.01)
N	825	825	250	825
R^2	0.23	0.22	0.10	0.22

***, **,*: statistically significant at 1, 5, 10 % level, respectively: robust standard error in brackets.

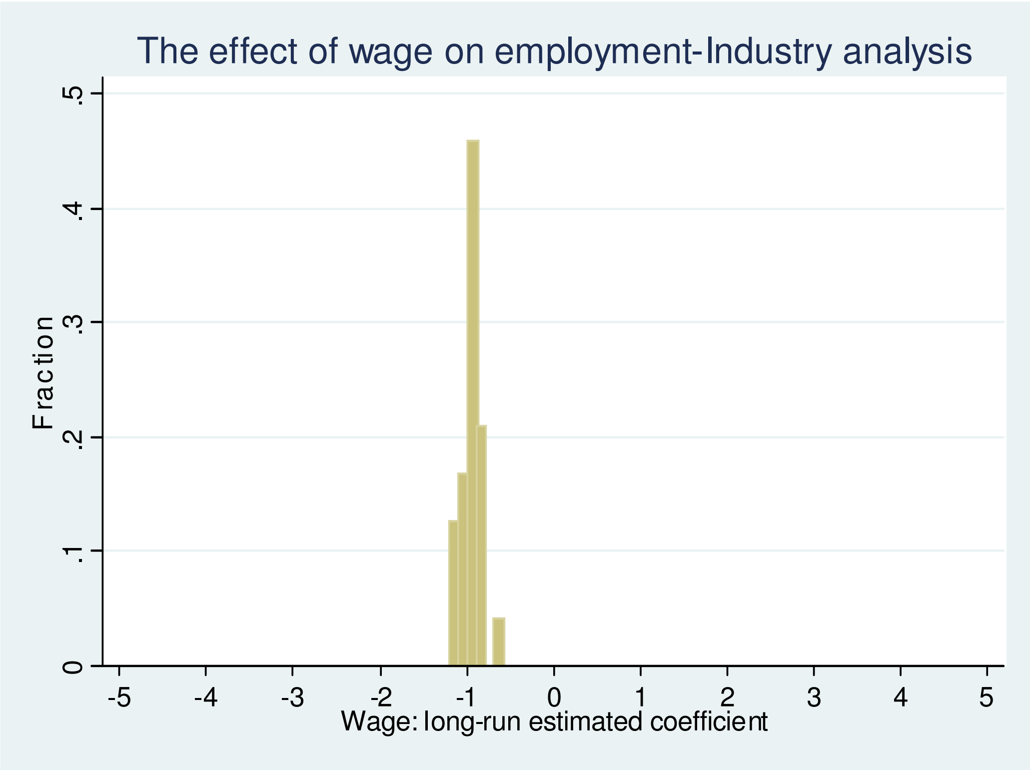

Figure 14: The effect of wage on employment.

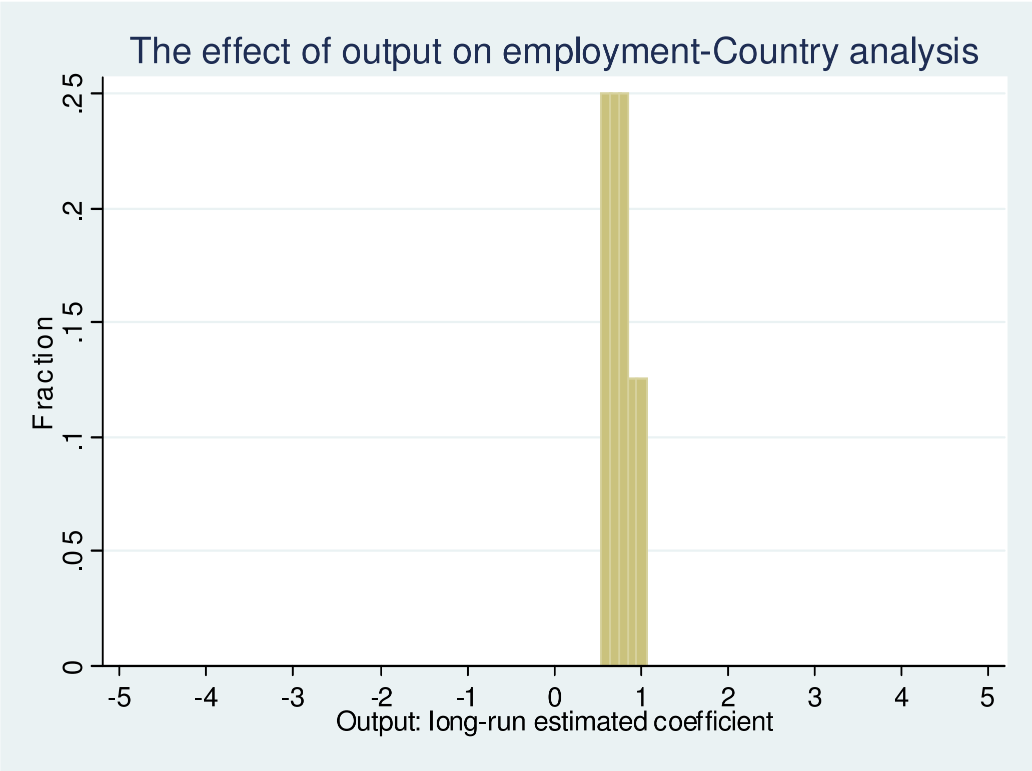

Figure 15: The effect of output on employment.

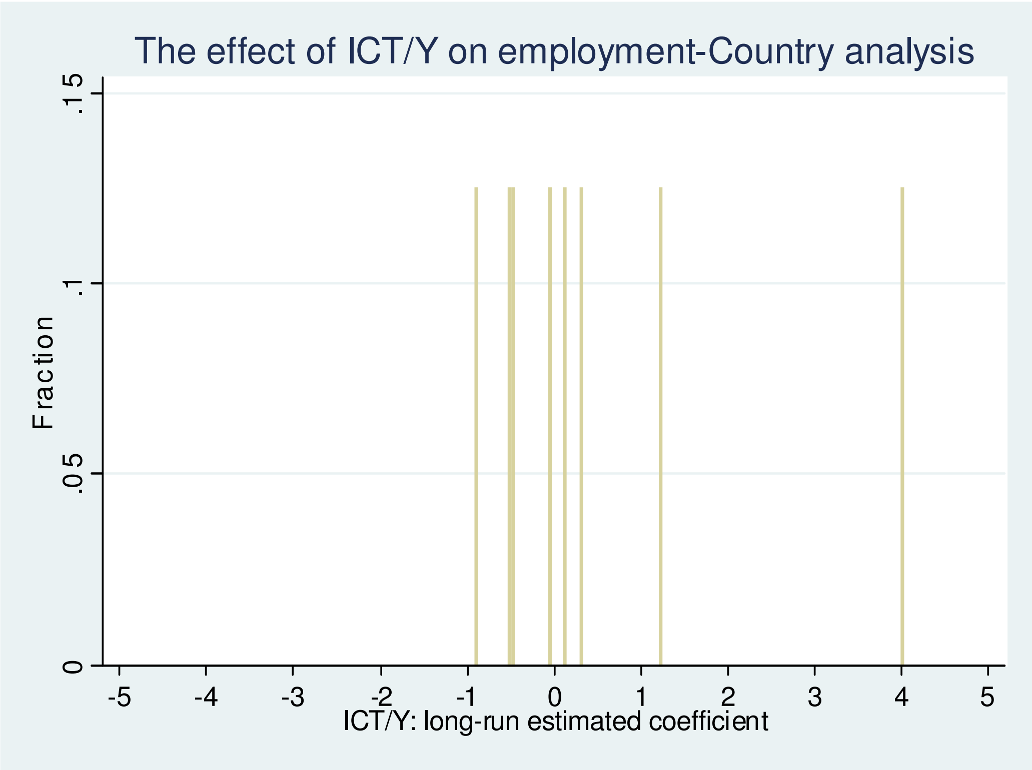

Figure 16: The effect of technology ($\frac{I_{ICT}}{Y}$) on employment.

Table 25: Non EU Countries , Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	AUS	JPN	KOR	USA
	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$
Long Run Regression				
lnw	-0.88***	-0.83***	-0.98***	-0.99***
	(0.03)	(0.02)	(0.01)	(0.02)
lnY	1.00	1.00	1.00	1.00
	.	.	.	.
$\frac{I_{ICT}}{Y}$	-0.57***	2.33***	0.43**	0.88***
	(0.13)	(0.34)	(0.15)	(0.12)
cons	-0.87***	-2.32***	-0.89***	-0.73***
	(0.11)	(0.18)	(0.11)	(0.07)
ECM				
Δlnw	-0.44***	-0.04	-0.54***	-0.30***
	(0.07)	(0.04)	(0.08)	(0.07)
ΔlnY	0.45***	0.12*	0.70***	0.42***
	(0.11)	(0.05)	(0.07)	(0.05)
$\Delta\frac{I_{ICT}}{Y}$	0.28**	0.64	0.40**	0.43**
	(0.09)	(0.58)	(0.11)	(0.14)
ϵ_{t-1}	-0.05***	-0.03	-0.11**	-0.07***
	(0.01)	(0.02)	(0.03)	(0.01)
cons	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
N	825	750	650	825
R^2	0.42	0.08	0.60	0.34

***, **,*: statistically significant at 1, 5, 10 % level, respectively: robust standard error in brackets.

Table 26: EU 15 Countries (1st part), Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	AUT	DNK	FIN	GER
	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$
Long Run Regression				
lnw	-0.99***	-0.88***	-1.09***	-0.93***
	(0.02)	(0.02)	(0.02)	(0.04)
lnY	1.00	1.00	1.00	1.00
	.	.	.	.
$\frac{I_{ICT}}{Y}$	-0.76***	0.60***	-2.12***	2.13***
	(0.13)	(0.09)	(0.24)	(0.22)
cons	-0.47***	-1.07***	-0.21***	-0.73***
	(0.07)	(0.10)	(0.05)	(0.13)
ECM				
Δlnw	-0.22**	-0.17**	-0.26***	-0.31**
	(0.07)	(0.05)	(0.07)	(0.10)
ΔlnY	0.20**	0.26***	0.42***	0.42***
	(0.06)	(0.05)	(0.07)	(0.10)
$\Delta\frac{I_{ICT}}{Y}$	0.60*	0.27	0.30	1.90**
	(0.23)	(0.15)	(0.21)	(0.54)
ϵ_{t-1}	-0.02	-0.03*	-0.07**	-0.14***
	(0.02)	(0.02)	(0.02)	(0.04)
cons	0.00	0.00	-0.00	-0.01
	(0.00)	(0.01)	(0.01)	(0.01)
N	675	825	825	300
R^2	0.20	0.19	0.35	0.41

***, **,*: statistically significant at 1, 5, 10 % level, respectively: robust standard error in brackets.

Table 27: EU 15 Countries (2nd part), Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	ITA	NLD	SWE	UK
	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$
Long Run Regression				
lnw	-1.02***	-0.88***	-0.88***	-0.82***
	(0.02)	(0.02)	(0.03)	(0.02)
lnY	1.00	1.00	1.00	1.00
	.	.	.	.
$\frac{I_{ICT}}{Y}$	-0.66**	-0.63***	1.73***	-0.99***
	(0.25)	(0.15)	(0.44)	(0.16)
cons	-0.67***	-0.99***	-1.24***	-0.97***
	(0.07)	(0.08)	(0.17)	(0.07)
N	850	850	300	850
ECM				
Δlnw	-0.30*	-0.33	-0.06	-0.15***
	(0.11)	(0.20)	(0.08)	(0.04)
ΔlnY	0.34**	0.31	-0.06	0.36***
	(0.11)	(0.16)	(0.12)	(0.06)
$\Delta \frac{I_{ICT}}{Y}$	0.21	0.30	0.50	0.21
	(0.27)	(0.16)	(0.34)	(0.19)
ϵ_{t-1}	-0.02	-0.11**	-0.12***	-0.04*
	(0.02)	(0.03)	(0.03)	(0.02)
cons	0.01	0.01	0.01	-0.01
	(0.01)	(0.00)	(0.01)	(0.01)
N	825	825	250	825
R^2	0.21	0.32	0.18	0.24

***, **,*: statistically significant at 1, 5, 10 % level, respectively: robust standard error in brackets.

Table 28: EU 15 countries (1st part) , Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	AUT	DNK	FIN	GER
	β/s.e.	β/s.e.	β/s.e.	β/s.e.
Long Run Regression				
lnw	-0.48	-0.60*	-0.69*	-0.82***
	(0.42)	(0.27)	(0.31)	(0.21)
lnY	0.80***	0.77***	0.73***	0.61***
	(0.10)	(0.11)	(0.07)	(0.09)
epl	-0.01	0.06	-0.05	0.05
	(0.04)	(0.07)	(0.04)	(0.03)
$\frac{I_{ICT}}{Y}$	-0.56	0.64	0.00	-1.17
	(0.45)	(1.08)	(1.38)	(2.43)
$cons$	-0.63	-0.59	0.53	2.93*
	(1.68)	(1.73)	(0.75)	(1.08)
N	525	525	525	300
R^2	0.74	0.75	0.72	0.86
ECM				
Δlnw	-0.30**	-0.17**	-0.15*	-0.30*
	(0.10)	(0.05)	(0.06)	(0.11)
ΔlnY	0.23**	0.20***	0.34***	0.44***
	(0.07)	(0.05)	(0.06)	(0.10)
Δepl	-0.00	0.02*	0.03***	0.00
	(0.01)	(0.01)	(0.01)	(0.00)
$\Delta \frac{I_{ICT}}{Y}$	0.58*	0.24	0.56	2.57**
	(0.22)	(0.13)	(0.38)	(0.84)
ϵ_{t-1}	-0.01	-0.00	-0.00	-0.03
	(0.01)	(0.01)	(0.01)	(0.02)
cons	0.00	0.01	-0.01	-0.01
	(0.00)	(0.00)	(0.01)	(0.01)
N	475	475	475	250
R^2	0.26	0.15	0.33	0.46

***, **,*: statistically significant at 1, 5, 10 % level, respectively: robust standard error in brackets.

Table 29: EU 15 countries (2nd part) , Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	ITA	NLD	SWE	UK
	β/s.e.	β/s.e.	β/s.e.	β/s.e.
Long Run Regression				
lnw	-0.89***	-1.04**	-0.71***	-0.84***
	(0.20)	(0.28)	(0.18)	(0.11)
lnY	0.58***	0.97***	0.83***	0.92***
	(0.08)	(0.06)	(0.05)	(0.04)
epl	0.04	0.01	0.00	-0.05
	(0.03)	(0.02)	(0.00)	(0.06)
$\frac{I_{ICT}}{Y}$	4.40**	1.44	0.14	0.49
	(1.39)	(1.69)	(1.50)	(0.80)
cons	2.71*	-0.34	-0.34	-0.21
	(1.15)	(0.96)	(1.08)	(0.52)
N	525	525	250	525
R^2	0.79	0.77	0.83	0.88
ECM				
Δlnw	-0.46**	-0.28	-0.03	-0.13**
	(0.15)	(0.19)	(0.08)	(0.04)
ΔlnY	0.47*	0.35*	-0.03	0.39***
	(0.17)	(0.14)	(0.13)	(0.05)
Δepl	-0.00	-0.02*	0.00	0.05***
	(0.00)	(0.01)	(0.00)	(0.01)
$\Delta \frac{I_{ICT}}{Y}$	0.49	0.26	0.91***	0.22
	(0.42)	(0.15)	(0.23)	(0.21)
ϵ_{t-1}	-0.03	-0.01	-0.01	0.01
	(0.02)	(0.01)	(0.01)	(0.02)
cons	0.01	0.01**	0.01	-0.01
	(0.00)	(0.00)	(0.01)	(0.01)
N	475	475	200	475
R^2	0.36	0.29	0.07	0.26

***, **,*: statistically significant at 1, 5, 10 % level, respectively: robust standard error in brackets.

Table 30: EU 15 countries (1st part) , Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	AUT	DNK	FIN	GER
	β/s.e.	β/s.e.	β/s.e.	β/s.e.
Long Run Regression				
lnw	-1.25***	-1.08***	-1.15***	-1.03***
	(0.07)	(0.14)	(0.07)	(0.10)
lnY	1.00***	0.98***	0.93***	1.07***
	(0.04)	(0.05)	(0.06)	(0.03)
RC	-0.14	-0.10	-0.28*	0.06
	(0.08)	(0.10)	(0.11)	(0.14)
$\frac{I_{ICT}}{Y}$	-0.85***	-0.68	-2.06**	-5.04***
	(0.06)	(0.33)	(0.53)	(0.45)
cons	0.48	0.30	0.57	-0.82
	(0.33)	(0.71)	(0.33)	(0.55)
N	378	392	392	168
R^2	0.96	0.95	0.91	0.96
ECM				
Δlnw	-0.15	-0.23*	-0.12**	-0.35**
	(0.08)	(0.08)	(0.04)	(0.10)
ΔlnY	0.17*	0.25*	0.28***	0.40***
	(0.06)	(0.09)	(0.04)	(0.09)
ΔRC	-0.32	-0.02	-0.07	0.13
	(0.16)	(0.05)	(0.11)	(0.10)
$\Delta\frac{I_{ICT}}{Y}$	0.23*	0.05	0.85***	1.19**
	(0.08)	(0.04)	(0.17)	(0.32)
ϵ_{t-1}	-0.01	-0.06***	-0.05*	-0.06
	(0.01)	(0.01)	(0.02)	(0.03)
cons	-0.01*	-0.00	-0.02**	-0.02***
	(0.00)	(0.00)	(0.00)	(0.00)
N	350	364	364	140
R^2	0.17	0.23	0.32	0.45

***, **,*: statistically significant at 1, 5, 10 % level, respectively: robust standard error in brackets.

Table 31: EU 15 countries (2nd part) , Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	ITA	NLD	SWE	UK
	β/s.e.	β/s.e.	β/s.e.	β/s.e.
Long Run Regression				
lnw	-1.09***	-1.07***	-0.68***	-1.01***
	(0.04)	(0.11)	(0.13)	(0.08)
lnY	1.03***	0.85***	0.88***	1.07***
	(0.05)	(0.05)	(0.06)	(0.04)
RC	0.31**	0.14	0.54*	-0.05
	(0.08)	(0.11)	(0.24)	(0.20)
$\frac{I_{ICT}}{Y}$	-1.38*	-0.79	-1.44*	-0.68**
	(0.63)	(0.56)	(0.55)	(0.20)
cons	-0.56	1.03	-1.04	-0.97*
	(0.48)	(0.49)	(0.63)	(0.34)
N	392	392	140	392
R^2	0.95	0.93	0.85	0.95
ECM				
	β/s.e.	β/s.e.	β/s.e.	β/s.e.
Δlnw	-0.18**	-0.15	0.04	-0.28**
	(0.06)	(0.08)	(0.05)	(0.08)
ΔlnY	0.21**	0.15*	-0.12	0.46***
	(0.05)	(0.06)	(0.06)	(0.05)
ΔRC	0.14*	-0.17	0.01	-0.19
	(0.05)	(0.13)	(0.16)	(0.20)
$\Delta \frac{I_{ICT}}{Y}$	0.16	0.06	1.03***	0.06
	(0.22)	(0.06)	(0.12)	(0.18)
ϵ_{t-1}	-0.02	-0.02	-0.03	-0.08**
	(0.01)	(0.01)	(0.02)	(0.02)
cons	-0.00	-0.00	0.00	-0.02***
	(0.00)	(0.00)	(0.01)	(0.00)
N	364	364	112	364
R^2	0.16	0.10	0.31	0.48

***, **,*: statistically significant at 1, 5, 10 % level, respectively: robust standard error in brackets.

Table 32: EU 15 countries (1st part) , Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	AUT	DNK	FIN	GER
	β/s.e.	β/s.e.	β/s.e.	β/s.e.
Long Run Regression				
lnw	-1.24***	-1.19***	-1.18***	-1.02***
	(0.07)	(0.15)	(0.07)	(0.10)
lnY	1.02***	0.99***	0.93***	1.07***
	(0.04)	(0.04)	(0.05)	(0.03)
RC	-0.17	-0.15	-0.37**	0.05
	(0.09)	(0.12)	(0.12)	(0.14)
epl	0.02	0.08*	-0.06	-0.01
	(0.02)	(0.03)	(0.03)	(0.01)
$\frac{I_{ICT}}{Y}$	-0.94***	0.10	-1.66***	-4.97***
	(0.06)	(0.32)	(0.32)	(0.45)
cons	0.25	0.59	0.77*	-0.81
	(0.29)	(0.74)	(0.27)	(0.56)
N	294	294	294	168
R^2	0.97	0.96	0.92	0.96
ECM				
Δlnw	-0.17	-0.28**	-0.10*	-0.35**
	(0.09)	(0.08)	(0.03)	(0.10)
ΔlnY	0.16*	0.22*	0.25***	0.40***
	(0.07)	(0.08)	(0.03)	(0.09)
ΔRC	-0.38	0.02	-0.08	0.13
	(0.21)	(0.07)	(0.11)	(0.12)
Δepl	-0.01*	0.01	0.03**	-0.00
	(0.01)	(0.01)	(0.01)	(0.00)
$\Delta \frac{I_{ICT}}{Y}$	0.24	0.06	1.00**	1.20**
	(0.12)	(0.04)	(0.27)	(0.30)
ϵ_{t-1}	-0.02	-0.08***	-0.03	-0.05
	(0.01)	(0.01)	(0.02)	(0.03)
cons	-0.01*	-0.00	-0.02***	-0.02***
	(0.00)	(0.00)	(0.00)	(0.00)
N	266	266	266	140
R^2	0.25	0.23	0.37	0.45

Table 33: EU 15 countries (2nd part) , Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	ITA	NLD	SWE	UK
	β/s.e.	β/s.e.	β/s.e.	β/s.e.
Long Run Regression				
lnw	-1.08***	-1.08***	-0.68***	-0.93***
	(0.10)	(0.16)	(0.13)	(0.12)
lnY	1.08***	0.85***	0.88***	1.03***
	(0.05)	(0.06)	(0.06)	(0.04)
RC	0.06	0.15	0.54*	0.00
	(0.15)	(0.12)	(0.24)	(0.27)
epl	0.05**	-0.03	0.00	0.04
	(0.02)	(0.03)	(0.00)	(0.04)
$\frac{I_{ICT}}{Y}$	-0.37	-0.94	-1.44*	-0.79**
	(0.97)	(0.61)	(0.55)	(0.21)
cons	-1.36**	1.13	-1.04	-0.91*
	(0.43)	(0.70)	(0.63)	(0.42)
N	294	294	140	294
R^2	0.96	0.92	0.85	0.95
ECM				
Δlnw	-0.22**	-0.08	0.04	-0.30**
	(0.07)	(0.09)	(0.05)	(0.09)
ΔlnY	0.19**	0.13*	-0.12	0.50***
	(0.06)	(0.04)	(0.06)	(0.05)
ΔRC	0.11*	-0.15	0.01	-0.20
	(0.05)	(0.12)	(0.16)	(0.26)
Δepl	-0.00	-0.05***	0.00	0.05
	(0.00)	(0.01)	(0.00)	(0.02)
$\Delta\frac{I_{ICT}}{Y}$	0.10	0.00	1.03***	-0.01
	(0.24)	(0.08)	(0.12)	(0.16)
ϵ_{t-1}	-0.02	-0.01	-0.03	-0.09***
	(0.02)	(0.02)	(0.02)	(0.02)
cons	-0.00	-0.00	0.00	-0.02***
	(0.00)	(0.00)	(0.01)	(0.00)
N	266	266	112	266
R^2	0.17	0.18	0.31	0.51

Figure 17: The effect of wage on employment.

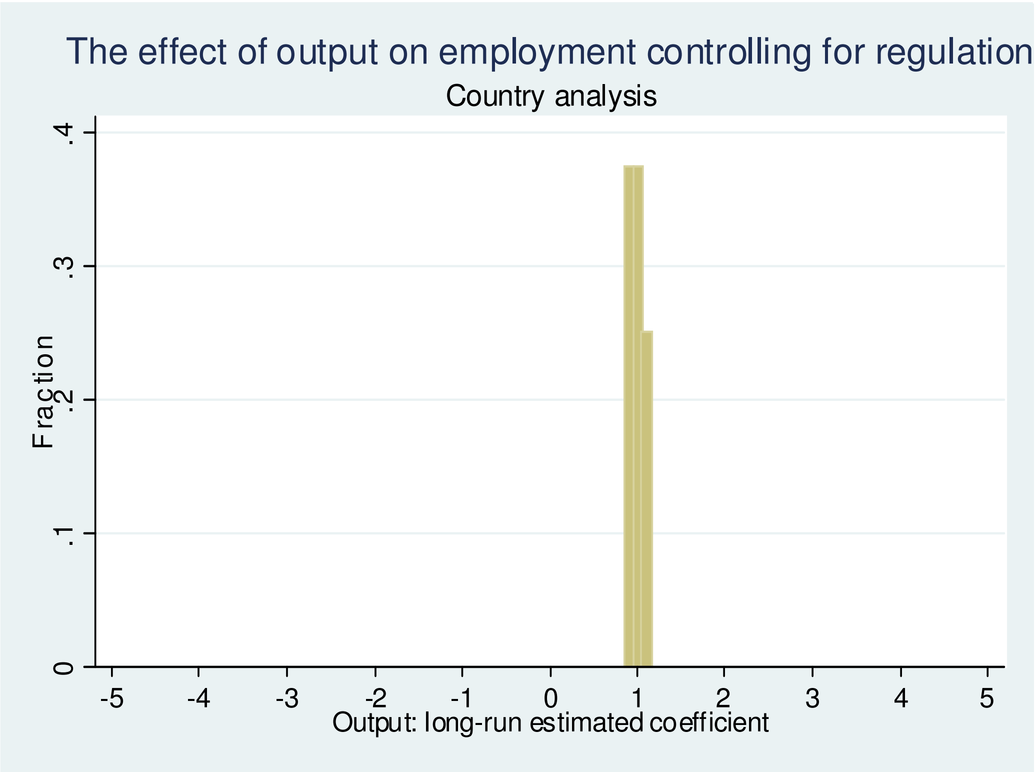

Figure 18: The effect of output on employment.

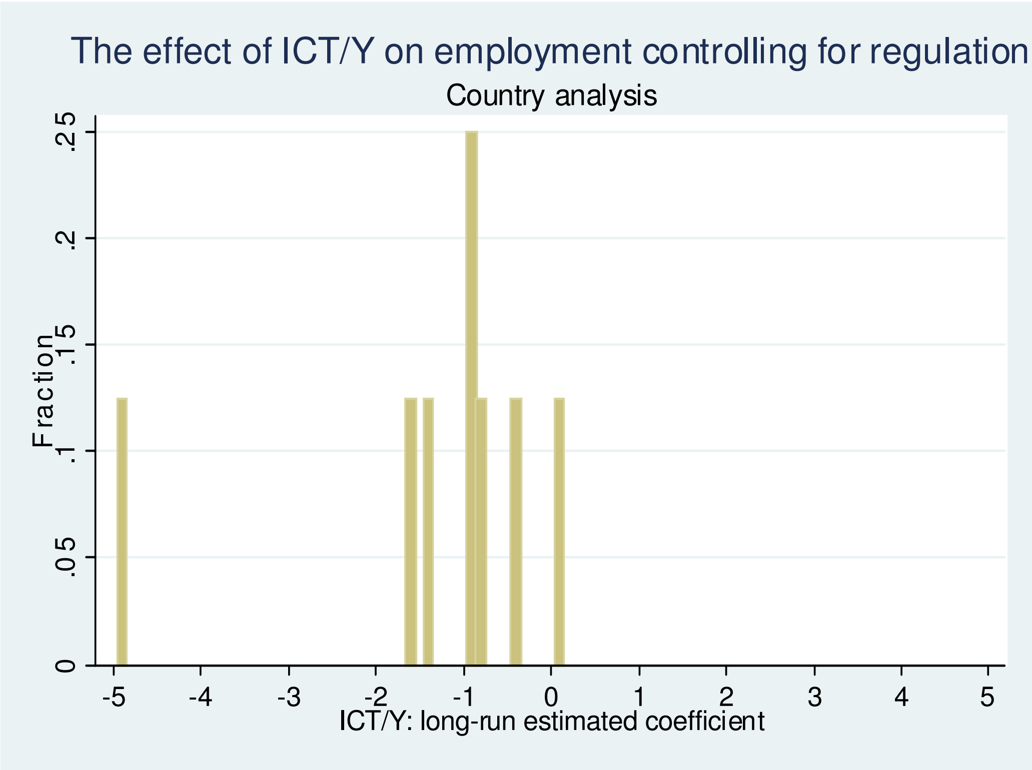

Figure 19: The effect of technology ($\frac{I_{ICT}}{Y}$) on employment.

Table 34: EU Countries (1st Part), Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	AUT	DNK	FIN	GER
	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$
Long Run Regression				
$\ln w$	-1.23***	-1.17***	-1.16***	-1.02***
	(0.08)	(0.18)	(0.08)	(0.10)
$\ln Y$	1.02***	1.02***	0.93***	1.07***
	(0.04)	(0.04)	(0.05)	(0.03)
RC	-0.18	-0.01	-0.50*	-0.12
	(0.10)	(0.12)	(0.21)	(0.29)
epl	0.02	0.07*	-0.06*	0.01
	(0.02)	(0.03)	(0.02)	(0.01)
$\frac{I_{ICT}}{Y} * RC$	0.60	-6.39**	6.62	6.24
	(0.71)	(1.96)	(9.53)	(7.99)
$\frac{I_{ICT}}{Y}$	-1.19**	1.48**	-4.02	-7.96
	(0.34)	(0.36)	(3.21)	(4.28)
cons	0.20	0.18	0.75*	-0.87
	(0.30)	(0.92)	(0.28)	(0.49)
ECM				
$\Delta \ln w$	-0.17	-0.28**	-0.10**	-0.36**
	(0.09)	(0.09)	(0.03)	(0.10)
$\Delta \ln Y$	0.16*	0.23*	0.25***	0.40***
	(0.07)	(0.08)	(0.03)	(0.09)
ΔRC	-0.54***	-0.04	-0.25*	0.05
	(0.11)	(0.08)	(0.11)	(0.20)
Δepl	-0.01*	0.01	0.03**	-0.00
	(0.00)	(0.01)	(0.01)	(0.00)
$\Delta \frac{I_{ICT}}{Y}$	-0.17	0.03	0.10	0.70
	(0.14)	(0.09)	(0.37)	(1.12)
$\Delta \left(\frac{I_{ICT}}{Y} * RC\right)$	1.49**	0.15	3.81**	1.22
	(0.38)	(0.33)	(0.92)	(2.23)
$\hat{\epsilon_{t-1}}$	-0.02	-0.09***	-0.03	-0.06
	(0.01)	(0.01)	(0.02)	(0.03)
cons	-0.01*	-0.00	-0.02***	-0.02***
	(0.00)	(0.00)	(0.00)	(0.00)
N	266	266	266	140

Table 35: EU Countries (2nd Part), Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	ITA	NLD	SWE	UK
Long Run Regression				
$\ln w$	-1.08***	-1.11***	-0.69***	-0.97***
	(0.10)	(0.17)	(0.14)	(0.11)
$\ln Y$	1.08***	0.85***	0.88***	1.03***
	(0.05)	(0.06)	(0.07)	(0.04)
RC	0.06	0.23	0.37	0.20
	(0.15)	(0.12)	(0.54)	(0.31)
epl	0.05**	-0.04	0.00	0.00
	(0.02)	(0.03)	(0.00)	(0.05)
$\frac{I_{ICT}}{Y} * RC$	-0.03	-2.06	2.26	-5.87
	(1.94)	(1.62)	(5.24)	(3.81)
$\frac{I_{ICT}}{Y}$	-0.36	-0.36	-2.01	1.16
	(1.33)	(0.93)	(1.76)	(1.24)
cons	-1.36**	1.17	-1.01	-0.76
	(0.45)	(0.72)	(0.66)	(0.38)
ECM				
$\Delta \ln w$	-0.22**	-0.08	0.04	-0.30**
	(0.07)	(0.09)	(0.05)	(0.09)
$\Delta \ln Y$	0.19**	0.13**	-0.12	0.50***
	(0.06)	(0.04)	(0.06)	(0.05)
ΔRC	-0.08	-0.13	-0.00	-0.10
	(0.07)	(0.14)	(0.31)	(0.31)
Δepl	-0.01	-0.05***	0.00	0.04
	(0.00)	(0.01)	(0.00)	(0.02)
$\Delta \frac{I_{ICT}}{Y}$	-0.48	0.08	0.98*	0.43
	(0.31)	(0.06)	(0.40)	(0.45)
$\Delta \left(\frac{I_{ICT}}{Y} * RC \right)$	1.60**	-0.33	0.18	-1.43
	(0.38)	(0.28)	(1.29)	(1.32)
$\hat{\epsilon}_{t-1}$	-0.02	-0.01	-0.03	-0.09***
	(0.02)	(0.02)	(0.02)	(0.02)
cons	-0.01	-0.00	0.00	-0.02***
	(0.00)	(0.00)	(0.01)	(0.00)
N	266	266	112	266
R^2	0.18	0.18	0.31	0.51

Table 36: Industries (1st part), Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	food	text	wood	pulp	coke	chemicals
	β/s.e.	β/s.e.	β/s.e.	β/s.e.	β/s.e.	β/s.e.
Long Run Regression						
lnw	-0.93***	-0.99***	-0.87***	-0.96***	-0.67**	-1.10***
	(0.04)	(0.02)	(0.05)	(0.05)	(0.17)	(0.08)
lnY	0.98***	0.94***	0.82***	0.99***	0.99***	1.05***
	(0.04)	(0.03)	(0.07)	(0.04)	(0.08)	(0.04)
$\frac{I_{ICT}}{Y}$	-1.13	-3.51	-0.49	-1.23***	-0.10	-1.10
	(0.88)	(1.57)	(2.05)	(0.19)	(0.38)	(1.02)
cons	-0.57	0.15	0.52	-0.53	-2.06***	-0.67
	(0.26)	(0.21)	(0.47)	(0.29)	(0.37)	(0.31)
N	235	235	235	235	225	235
R^2	0.98	0.99	0.93	0.97	0.83	0.97
ECM						
Δlnw	-0.23***	-0.44***	-0.20***	-0.14*	0.01	-0.20**
	(0.04)	(0.07)	(0.04)	(0.04)	(0.02)	(0.05)
ΔlnY	0.17***	0.61***	0.29***	0.19*	0.02	0.17*
	(0.02)	(0.05)	(0.01)	(0.06)	(0.02)	(0.05)
$\Delta\frac{I_{ICT}}{Y}$	0.24	0.14	0.05	0.06	-0.03	0.01
	(0.20)	(0.37)	(0.51)	(0.09)	(0.05)	(0.09)
ϵ_{t-1}	-0.05**	-0.08*	-0.04***	-0.03*	-0.00	-0.04
	(0.01)	(0.03)	(0.01)	(0.01)	(0.01)	(0.03)
cons	-0.01**	-0.02***	-0.01***	-0.01***	-0.01	-0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
N	223	223	223	223	214	223
R^2	0.23	0.63	0.34	0.18	0.02	0.20

***, **,*: statistically significant at 1, 5, 10 % level, respectively: robust standard error in brackets.

Table 37: Industries (2nd part), Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	rubber	othernonmetal	basicmetal	machinery	electrical	transporteq
	β/s.e.	β/s.e.	β/s.e.	β/s.e.	β/s.e.	β/s.e.
Long Run Regression						
lnw	-0.98***	-0.93***	-0.98***	-0.97***	-0.98***	-1.05***
	(0.02)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
lnY	0.99***	1.01***	1.00***	1.00***	0.99***	1.05***
	(0.03)	(0.04)	(0.03)	(0.03)	(0.05)	(0.03)
$\frac{I_{ICT}}{Y}$	-0.48	-1.12	-1.43	-0.67*	0.33	-2.02*
	(1.03)	(0.51)	(1.05)	(0.23)	(1.01)	(0.66)
cons	-0.36	-0.75**	-0.50*	-0.41*	-0.38	-0.44*
	(0.18)	(0.20)	(0.18)	(0.15)	(0.42)	(0.18)
N	235	235	235	235	235	235
R^2	0.99	0.99	0.99	0.99	0.94	0.99
ECM						
Δlnw	-0.39***	-0.34***	-0.27**	-0.38***	-0.02	-0.20**
	(0.05)	(0.04)	(0.06)	(0.04)	(0.10)	(0.06)
ΔlnY	0.40***	0.39***	0.30***	0.44***	0.04	0.26***
	(0.04)	(0.04)	(0.05)	(0.03)	(0.14)	(0.02)
$\Delta\frac{I_{ICT}}{Y}$	0.03	0.40	0.35	0.30	0.48	0.40
	(0.28)	(0.43)	(0.25)	(0.30)	(0.24)	(0.22)
ϵ_{t-1}	-0.11**	-0.11**	-0.13***	-0.13***	-0.06*	-0.11***
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.00)
cons	-0.00	-0.01*	-0.01*	-0.01***	-0.02*	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
N	223	223	223	223	223	223
R^2	0.44	0.51	0.46	0.55	0.15	0.38

***, **,*: statistically significant at 1, 5, 10 % level, respectively: robust standard error in brackets.

Table 38: Industries (3rd part), Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	manufacturing	sale	wholesale	retail	transport	post
	β/s.e.	β/s.e.	β/s.e.	β/s.e.	β/s.e.	β/s.e.
Long Run Regression						
lnw	-0.89***	-0.92***	-0.84***	-0.92***	-1.09***	-0.97***
	(0.06)	(0.10)	(0.10)	(0.09)	(0.03)	(0.06)
lnY	0.92***	0.94***	0.84***	0.84***	1.16***	0.96***
	(0.06)	(0.10)	(0.11)	(0.12)	(0.07)	(0.06)
$\frac{I_{ICT}}{Y}$	-1.49	1.89**	2.07	3.57	-2.87**	-0.30
	(0.93)	(0.52)	(1.51)	(2.00)	(0.68)	(0.44)
cons	-0.02	-0.37	0.35	0.60	-1.64*	-0.39
	(0.43)	(0.49)	(0.66)	(0.79)	(0.59)	(0.41)
R^2	0.96	0.95	0.92	0.92	0.97	0.93
ECM						
Δlnw	-0.41***	-0.25*	-0.20*	-0.23**	-0.20	-0.06
	(0.08)	(0.10)	(0.07)	(0.05)	(0.09)	(0.06)
ΔlnY	0.43***	0.25	0.29**	0.27	0.25*	0.24*
	(0.07)	(0.12)	(0.09)	(0.12)	(0.10)	(0.08)
$\Delta \frac{I_{ICT}}{Y}$	-0.19*	0.40**	0.25	0.30	0.18	0.15
	(0.07)	(0.09)	(0.19)	(0.14)	(0.10)	(0.08)
ϵ_{t-1}	-0.03	-0.04*	-0.02*	-0.02***	-0.01	0.03**
	(0.02)	(0.02)	(0.01)	(0.00)	(0.02)	(0.01)
cons	-0.00	0.00	0.00	0.01	0.00	-0.01**
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
N	223	223	223	223	223	223
R^2	0.40	0.26	0.27	0.27	0.18	0.16

***, **,*: statistically significant at 1, 5, 10 % level, respectively: robust standard error in brackets.

Table 39: Industries (4th part), Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	agriculture	mining	electricity	construction	hotels	financial	tot
Long Run Regression							
	β/s.e.	β/s.e.	β/s.e.	β/s.e.	β/s.e.	β/s.e.	β/s.e.
lnw	-1.09***	-1.19***	-1.18***	-0.83***	-0.86***	-1.06***	-0.96***
	(0.05)	(0.17)	(0.06)	(0.03)	(0.02)	(0.03)	(0.04)
lnY	1.40***	0.75**	1.08***	0.87***	0.88***	1.01***	0.98***
	(0.10)	(0.19)	(0.05)	(0.05)	(0.07)	(0.04)	(0.04)
$\frac{I_{ICT}}{Y}$	5.86	-3.39	-5.26*	-2.65*	2.96	-0.46*	-0.17
	(2.68)	(4.78)	(2.20)	(0.81)	(1.99)	(0.19)	(0.28)
cons	-4.96***	0.88	-0.92	0.28	0.00	-0.40	-0.35
	(0.93)	(1.20)	(0.44)	(0.40)	(0.60)	(0.39)	(0.30)
R^2	0.94	0.63	0.95	0.98	0.97	0.97	0.99
ECM							
Δlnw	-0.18	-0.07**	-0.09	-0.52***	-0.22	-0.02	-0.18**
	(0.10)	(0.02)	(0.05)	(0.08)	(0.10)	(0.04)	(0.05)
ΔlnY	0.16	-0.11	0.09*	0.64***	0.28**	0.10	0.56***
	(0.08)	(0.09)	(0.03)	(0.08)	(0.08)	(0.11)	(0.09)
$\Delta\frac{I_{ICT}}{Y}$	1.94*	0.43**	-0.66***	0.31	0.38	-0.05	0.52*
	(0.80)	(0.13)	(0.11)	(0.75)	(0.23)	(0.16)	(0.16)
ϵ_{t-1}	-0.02	-0.03**	0.00	-0.03	-0.03	-0.00	-0.04**
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.04)	(0.01)
cons	-0.01	-0.03**	-0.01**	-0.01	0.02***	0.01	-0.01
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
N	223	223	223	223	223	223	223
R^2	0.12	0.19	0.09	0.56	0.20	0.03	0.51

***, **,*: statistically significant at 1, 5, 10 % level, respectively: robust standard error in brackets.

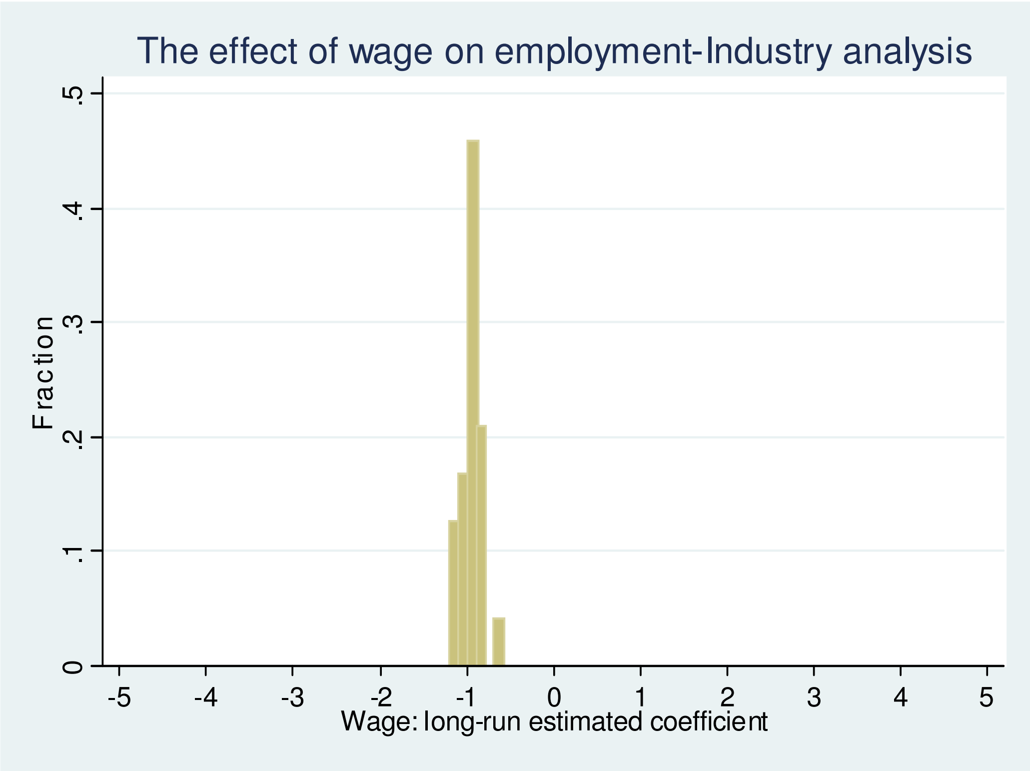

Figure 20: The effect of wage on employment.

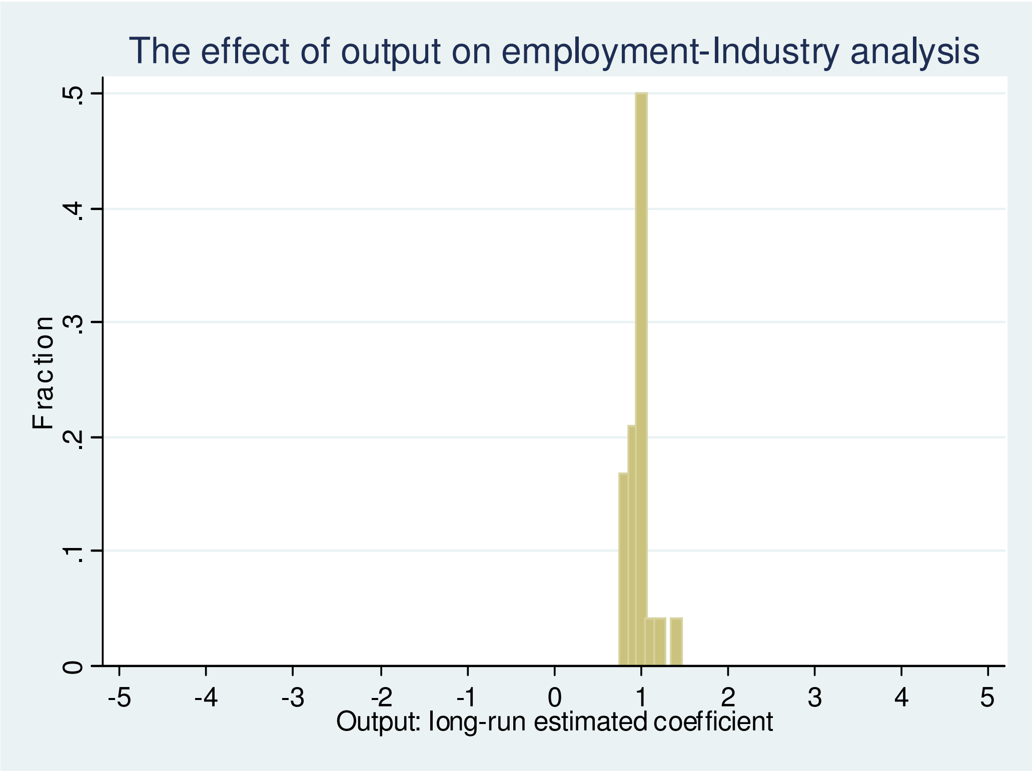

Figure 21: The effect of output on employment.

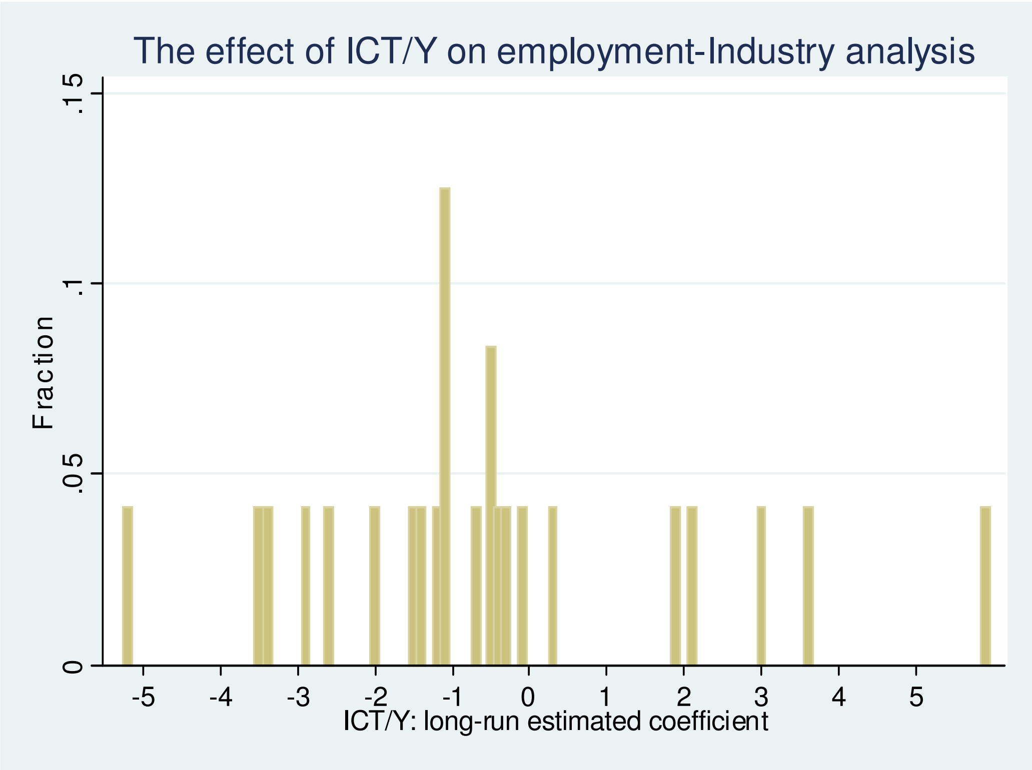

Figure 22: The effect of technology ($\frac{I_{ICT}}{Y}$) on employment.

Table 40: Industry (1st part) , Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	food	text	wood	pulp	coke	chemicals
	β/s.e.	β/s.e.	β/s.e.	β/s.e.	β/s.e.	β/s.e.
Long Run Regression						
lnw	-0.91***	-0.97***	-0.87***	-0.96***	-0.75***	-1.12***
	(0.03)	(0.01)	(0.05)	(0.05)	(0.12)	(0.08)
lnY	1.00***	0.99***	0.89***	1.03***	1.01***	1.04***
	(0.04)	(0.02)	(0.07)	(0.05)	(0.06)	(0.05)
epl	-0.03	-0.05**	-0.02	-0.03	-0.09*	0.02
	(0.03)	(0.01)	(0.02)	(0.02)	(0.03)	(0.03)
$\frac{I_{ICT}}{Y}$	-1.37	-2.53	-0.78	-0.70*	0.01	0.22
	(0.86)	(1.39)	(1.48)	(0.23)	(0.25)	(1.18)
cons	-0.69*	-0.17	0.00	-0.79	-1.77**	-0.61
	(0.23)	(0.13)	(0.38)	(0.35)	(0.41)	(0.31)
N	174	174	174	174	164	174
R^2	0.99	1.00	0.95	0.97	0.85	0.98
ECM						
Δlnw	-0.24***	-0.55***	-0.21**	-0.15	0.01	-0.19*
	(0.04)	(0.06)	(0.05)	(0.07)	(0.02)	(0.08)
ΔlnY	0.15*	0.63***	0.24***	0.16**	0.02	0.17**
	(0.05)	(0.05)	(0.02)	(0.04)	(0.03)	(0.05)
Δepl	0.00	-0.01	-0.00	-0.00	-0.02	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
$\Delta \frac{I_{ICT}}{Y}$	0.25	0.19	0.11	0.08	-0.03	0.07
	(0.25)	(0.41)	(0.53)	(0.07)	(0.05)	(0.13)
ϵ_{t-1}	-0.04	-0.11	-0.09	-0.03	-0.01	-0.04
	(0.02)	(0.06)	(0.04)	(0.01)	(0.03)	(0.03)
cons	-0.01**	-0.02***	-0.01	-0.01*	-0.02	-0.01*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
N	157	157	157	157	148	157
R^2	0.25	0.65	0.30	0.19	0.05	0.20

***, **,*: statistically significant at 1, 5, 10 % level, respectively: robust standard error in brackets.

Table 41: Industry (2nd part) , Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	rubber	othernonmetal	basicmetal	machinery	electrical
	β/s.e.	β/s.e.	β/s.e.	β/s.e.	β/s.e.
Long Run Regression					
lnw	-0.98***	-0.92***	-0.99***	-0.99***	-0.98***
	(0.01)	(0.02)	(0.04)	(0.03)	(0.05)
lnY	1.01***	1.04***	1.03***	1.04***	1.03***
	(0.02)	(0.03)	(0.03)	(0.02)	(0.06)
epl	-0.02	-0.03	-0.03*	-0.04*	-0.01
	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
$\frac{I_{ICT}}{Y}$	-0.09	0.07	-0.93	-0.82	1.16
	(1.17)	(0.79)	(1.32)	(0.39)	(1.42)
cons	-0.56**	-1.01**	-0.67**	-0.59**	-0.76
	(0.14)	(0.22)	(0.18)	(0.13)	(0.55)
N	174	174	174	174	174
R^2	0.99	0.99	0.99	0.99	0.93
ECM					
Δlnw	-0.42***	-0.42***	-0.31**	-0.45***	-0.01
	(0.05)	(0.04)	(0.09)	(0.05)	(0.10)
ΔlnY	0.42***	0.41***	0.29**	0.41***	0.03
	(0.06)	(0.04)	(0.06)	(0.03)	(0.14)
Δepl	0.00	0.00	0.01	-0.00	0.01
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
$\Delta\frac{I_{ICT}}{Y}$	-0.13	0.56	0.38	0.28	0.51
	(0.25)	(0.44)	(0.26)	(0.24)	(0.24)
ϵ_{t-1}	-0.14**	-0.17***	-0.14**	-0.15***	-0.06*
	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)
cons	0.00	-0.01*	-0.01	-0.01*	-0.02
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
N	157	157	157	157	157
R^2	0.47	0.61	0.44	0.56	0.18

***, **,*: statistically significant at 1, 5, 10 % level, respectively: robust standard error in brackets.

Table 42: Industry (2nd part) , Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	manufacturing	sale	wholesale	retail	transport	post
	β/s.e.	β/s.e.	β/s.e.	β/s.e.	β/s.e.	β/s.e.
Long Run Regression						
lnw	-0.90***	-0.92***	-0.86***	-0.88***	-1.08***	-0.95***
	(0.07)	(0.06)	(0.07)	(0.07)	(0.03)	(0.04)
lnY	0.97***	1.02***	0.93***	0.93***	1.16***	1.01***
	(0.05)	(0.06)	(0.07)	(0.06)	(0.08)	(0.06)
epl	-0.04	-0.09	-0.07	-0.10	-0.02	-0.03
	(0.03)	(0.04)	(0.05)	(0.06)	(0.02)	(0.04)
$\frac{I_{ICT}}{Y}$	-1.75	1.04	0.95	1.89	-2.61**	0.08
	(1.00)	(0.54)	(0.82)	(0.93)	(0.66)	(0.45)
cons	-0.30	-0.84	-0.28	-0.08	-1.60	-0.97*
	(0.33)	(0.43)	(0.54)	(0.49)	(0.70)	(0.38)
N	174	174	174	174	174	174
R^2	0.96	0.97	0.94	0.95	0.97	0.95
ECM						
Δlnw	-0.44***	-0.38**	-0.28**	-0.36***	-0.23*	-0.06
	(0.08)	(0.09)	(0.08)	(0.05)	(0.09)	(0.08)
ΔlnY	0.40***	0.33**	0.38**	0.37*	0.26	0.27*
	(0.08)	(0.07)	(0.09)	(0.12)	(0.14)	(0.09)
Δepl	-0.00	0.02**	0.01	0.00	0.00	0.01
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
$\Delta\frac{I_{ICT}}{Y}$	-0.14	0.16	0.33	0.21	0.17	0.15
	(0.09)	(0.08)	(0.18)	(0.11)	(0.12)	(0.09)
ϵ_{t-1}	-0.03	-0.05*	-0.03*	-0.02*	-0.00	0.01
	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)
cons	-0.00	0.01**	0.00	0.01	0.00	-0.02**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
N	157	157	157	157	157	157
R^2	0.42	0.42	0.38	0.36	0.15	0.16

***, **,*: statistically significant at 1, 5, 10 % level, respectively: robust standard error in brackets.

Table 43: Industry (3rd part) , Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	agriculture	mining	electricity	construction	hotels	financial	tot
	β/s.e.	β/s.e.	β/s.e.	β/s.e.	β/s.e.	β/s.e.	β/s.e.
Long Run Regression							
lnw	-1.09***	-0.97***	-1.20***	-0.82***	-0.89***	-1.06***	-0.96***
	(0.07)	(0.13)	(0.04)	(0.04)	(0.04)	(0.04)	(0.02)
lnY	1.41***	0.72**	1.04***	0.89***	0.92***	1.05***	1.01***
	(0.15)	(0.16)	(0.05)	(0.05)	(0.08)	(0.04)	(0.02)
epl	-0.01	0.07	0.03	-0.00	-0.02	-0.01	-0.04*
	(0.05)	(0.20)	(0.02)	(0.03)	(0.04)	(0.02)	(0.01)
$\frac{I_{ICT}}{Y}$	4.91	-5.99	-3.32*	-1.68	2.44	-0.68***	-0.28
	(2.85)	(2.71)	(1.15)	(1.04)	(1.45)	(0.13)	(0.25)
cons	-5.07**	0.29	-0.62	0.05	-0.20	-0.78	-0.67*
	(1.20)	(1.13)	(0.47)	(0.39)	(0.67)	(0.43)	(0.20)
N	174	174	174	174	174	174	174
R^2	0.93	0.66	0.96	0.98	0.97	0.97	1.00
ECM							
	β/s.e.	β/s.e.	β/s.e.	β/s.e.	β/s.e.	β/s.e.	β/s.e.
Δlnw	-0.09	-0.07**	-0.13*	-0.59***	-0.19	0.04	-0.17*
	(0.05)	(0.01)	(0.05)	(0.08)	(0.10)	(0.02)	(0.06)
ΔlnY	0.08	0.00	0.09*	0.66***	0.34**	0.12	0.65***
	(0.06)	(0.09)	(0.03)	(0.06)	(0.09)	(0.11)	(0.07)
Δepl	-0.00	0.02	0.01	0.01	0.01**	0.00	0.00*
	(0.01)	(0.02)	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)
$\Delta\frac{I_{ICT}}{Y}$	1.26*	0.30**	-0.52**	0.06	0.10	0.15	0.43
	(0.43)	(0.06)	(0.11)	(0.70)	(0.25)	(0.11)	(0.20)
ϵ_{t-1}	-0.03	-0.05**	0.00	-0.04	-0.04*	0.00	-0.07**
	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)	(0.01)
cons	-0.01	-0.03**	-0.01**	-0.00	0.02***	-0.00	-0.01*
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
N	157	157	157	157	157	157	157
R^2	0.06	0.39	0.11	0.61	0.30	0.08	0.57

***, **,*: statistically significant at 1, 5, 10 % level, respectively: robust standard error in brackets.

Table 44: Industry (4th part) , Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	food	text	wood	pulp	coke	chemicals
	β/s.e.	β/s.e.	β/s.e.	β/s.e.	β/s.e.	β/s.e.
Long Run Regression						
lnw	-0.90***	-0.97***	-0.87***	-0.97***	-0.72***	-1.12***
	(0.04)	(0.01)	(0.06)	(0.04)	(0.12)	(0.09)
lnY	0.96***	0.96***	0.86***	1.08***	0.99***	1.04***
	(0.05)	(0.02)	(0.09)	(0.08)	(0.05)	(0.06)
epl	-0.03	-0.04*	-0.01	-0.03	-0.09**	0.02
	(0.02)	(0.01)	(0.03)	(0.02)	(0.03)	(0.03)
RC	-1.44	-1.71	-1.39	2.72	0.69	-0.89
	(1.54)	(0.81)	(1.53)	(1.29)	(1.29)	(1.90)
$\frac{I_{ICT}}{Y}$	-3.03	-5.63*	-1.58	-0.11	0.01	-1.75
	(2.30)	(1.71)	(2.12)	(0.67)	(0.26)	(2.03)
cons	-0.13	0.27	0.40	-1.61	-1.78**	-0.37
	(0.53)	(0.25)	(0.73)	(0.81)	(0.34)	(0.62)
N	148	148	148	148	148	148
R^2	0.99	1.00	0.96	0.97	0.87	0.98
ECM						
Δlnw	-0.24**	-0.54***	-0.25**	-0.15	0.01	-0.21*
	(0.05)	(0.06)	(0.06)	(0.06)	(0.02)	(0.08)
ΔlnY	0.17*	0.60***	0.23***	0.13*	0.01	0.17*
	(0.06)	(0.05)	(0.02)	(0.04)	(0.02)	(0.05)
Δepl	0.00	-0.00	0.00	-0.00	0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
$\Delta \frac{I_{ICT}}{Y}$	0.56	-0.15	0.10	0.21	0.02	0.01
	(0.26)	(0.74)	(0.50)	(0.15)	(0.03)	(0.11)
ΔRC	0.48	2.79	-0.55	1.95	1.12	1.11
	(0.57)	(1.51)	(0.62)	(0.85)	(2.30)	(0.50)
ϵ_{t-1}	-0.04	-0.15*	-0.11*	-0.07*	-0.03	-0.05
	(0.03)	(0.06)	(0.05)	(0.02)	(0.02)	(0.04)
cons	-0.01**	-0.02**	-0.01	-0.01	-0.01*	-0.00
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)
R^2	0.25	0.68	0.36	0.24	0.05	0.23
N	132	132	132	132	132	132

***, **,*: statistically significant at 1, 5, 10 % level, respectively; robust standard error in brackets

Table 45: Industry (5th part) , Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	rubber	othernonmetal	basicmetal	machinery	electrical
	β/s.e.	β/s.e.	β/s.e.	β/s.e.	β/s.e.
Long Run Regression					
lnw	-0.98***	-0.93***	-0.97***	-1.00***	-0.99***
	(0.02)	(0.02)	(0.04)	(0.02)	(0.04)
lnY	1.01***	1.02***	1.05***	1.08***	1.23***
	(0.03)	(0.03)	(0.05)	(0.02)	(0.10)
epl	-0.02	-0.03*	-0.04**	-0.05**	-0.12
	(0.02)	(0.01)	(0.01)	(0.01)	(0.05)
RC	0.29	-0.53	0.44	1.56*	6.24
	(0.60)	(0.48)	(1.34)	(0.66)	(3.14)
$\frac{I_{ICT}}{Y}$	-0.57	-1.17	-1.97	-0.44	-0.21
	(1.47)	(1.06)	(1.09)	(0.35)	(1.34)
cons	-0.55	-0.75*	-0.95	-1.06**	-3.04*
	(0.29)	(0.25)	(0.62)	(0.24)	(1.19)
N	148	148	148	148	148
R^2	0.99	1.00	0.99	1.00	0.95
ECM					
Δlnw	-0.40***	-0.42***	-0.33*	-0.50***	-0.01
	(0.06)	(0.04)	(0.10)	(0.07)	(0.09)
ΔlnY	0.40***	0.42***	0.29**	0.44***	0.11
	(0.06)	(0.02)	(0.07)	(0.04)	(0.12)
Δepl	0.00	0.01	0.01	-0.00	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$\Delta\frac{I_{ICT}}{Y}$	0.15	1.25**	0.40	0.30	1.14*
	(0.46)	(0.34)	(0.46)	(0.23)	(0.41)
ΔRC	0.60	0.16	-1.30	-0.23	-0.45
	(1.28)	(1.07)	(1.26)	(2.28)	(3.09)
ϵ_{t-1}	-0.15**	-0.23**	-0.15***	-0.17***	-0.05
	(0.03)	(0.06)	(0.02)	(0.02)	(0.05)
cons	0.00	-0.01*	-0.01	-0.01	-0.02
	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)
N	132	132	132	132	132
R^2	0.46	0.67	0.47	0.58	0.23

***, **,*: statistically significant at 1, 5, 10 % level, respectively; robust standard error in brackets

Table 46: Industry (3rd part) , Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	manufacturing	transport	post
	β/s.e.	β/s.e.	β/s.e.
Long Run Regression			
lnw	-0.89***	-1.10***	-0.93***
	(0.08)	(0.02)	(0.02)
lnY	0.96***	1.25***	1.01***
	(0.08)	(0.07)	(0.04)
epl	-0.04	-0.05**	-0.02
	(0.03)	(0.01)	(0.02)
RC	-0.71	0.38*	0.90***
	(2.23)	(0.15)	(0.16)
$\frac{I_{ICT}}{Y}$	-2.71	-2.30***	0.68
	(1.91)	(0.38)	(0.37)
cons	-0.19	-2.64**	-1.53**
	(0.75)	(0.72)	(0.35)
N	148	148	148
R^2	0.97	0.98	0.97
ECM			
Δlnw	-0.44**	-0.29*	-0.07
	(0.09)	(0.09)	(0.08)
ΔlnY	0.40**	0.30	0.31**
	(0.09)	(0.14)	(0.08)
Δepl	-0.00	0.00	0.01
	(0.01)	(0.01)	(0.02)
$\Delta \frac{I_{ICT}}{Y}$	-0.18*	0.26	0.19
	(0.07)	(0.17)	(0.13)
ΔRC	1.29	0.04	0.18
	(1.62)	(0.08)	(0.09)
ϵ_{t-1}	-0.03	-0.03	-0.01
	(0.02)	(0.03)	(0.01)
cons	-0.00	0.00	-0.02*
	(0.00)	(0.01)	(0.01)
N	132	132	132
R^2	0.44	0.22	0.19

***, **,*: statistically significant at 1, 5, 10 % level, respectively; robust standard error in brackets

Table 47: Industry (4th part) , Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	food	text	wood	pulp	coke	chemicals
	β/s.e.	β/s.e.	β/s.e.	β/s.e.	β/s.e.	β/s.e.
Long Run Regression						
lnw	-0.90***	-0.97***	-0.87***	-0.97***	-0.72***	-1.12***
	(0.04)	(0.01)	(0.06)	(0.04)	(0.12)	(0.09)
lnY	0.96***	0.96***	0.86***	1.08***	0.99***	1.04***
	(0.05)	(0.02)	(0.09)	(0.08)	(0.05)	(0.06)
epl	-0.03	-0.04*	-0.01	-0.03	-0.09**	0.02
	(0.02)	(0.01)	(0.03)	(0.02)	(0.03)	(0.03)
RC	-1.44	-1.71	-1.39	2.72	0.69	-0.89
	(1.54)	(0.81)	(1.53)	(1.29)	(1.29)	(1.90)
$\frac{I_{ICT}}{Y}$	-3.03	-5.63*	-1.58	-0.11	0.01	-1.75
	(2.30)	(1.71)	(2.12)	(0.67)	(0.26)	(2.03)
cons	-0.13	0.27	0.40	-1.61	-1.78**	-0.37
	(0.53)	(0.25)	(0.73)	(0.81)	(0.34)	(0.62)
N	148	148	148	148	148	148
R^2	0.99	1.00	0.96	0.97	0.87	0.98
ECM						
Δlnw	-0.24**	-0.54***	-0.25**	-0.15	0.01	-0.21*
	(0.05)	(0.06)	(0.06)	(0.06)	(0.02)	(0.08)
ΔlnY	0.17*	0.60***	0.23***	0.13*	0.01	0.17*
	(0.06)	(0.05)	(0.02)	(0.04)	(0.02)	(0.05)
Δepl	0.00	-0.00	0.00	-0.00	0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
$\Delta\frac{I_{ICT}}{Y}$	0.56	-0.15	0.10	0.21	0.02	0.01
	(0.26)	(0.74)	(0.50)	(0.15)	(0.03)	(0.11)
ΔRC	0.48	2.79	-0.55	1.95	1.12	1.11
	(0.57)	(1.51)	(0.62)	(0.85)	(2.30)	(0.50)
ϵ_{t-1}	-0.04	-0.15*	-0.11*	-0.07*	-0.03	-0.05
	(0.03)	(0.06)	(0.05)	(0.02)	(0.02)	(0.04)
cons	-0.01**	-0.02**	-0.01	-0.01	-0.01*	-0.00
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)
N	132	132	132	132	132	132
R^2	0.25	0.68	0.36	0.24	0.05	0.23

***, **,*: statistically significant at 1, 5, 10 % level, respectively; robust standard error in brackets

Table 48: Industry (5th part) , Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	rubber	othernonmetal	basicmetal	machinery	electrical
	β/s.e.	β/s.e.	β/s.e.	β/s.e.	β/s.e.
Long Run Regression					
lnw	-0.98***	-0.93***	-0.97***	-1.00***	-0.99***
	(0.02)	(0.02)	(0.04)	(0.02)	(0.04)
lnY	1.01***	1.02***	1.05***	1.08***	1.23***
	(0.03)	(0.03)	(0.05)	(0.02)	(0.10)
epl	-0.02	-0.03*	-0.04**	-0.05**	-0.12
	(0.02)	(0.01)	(0.01)	(0.01)	(0.05)
RC	0.29	-0.53	0.44	1.56*	6.24
	(0.60)	(0.48)	(1.34)	(0.66)	(3.14)
$\frac{I_{ICT}}{Y}$	-0.57	-1.17	-1.97	-0.44	-0.21
	(1.47)	(1.06)	(1.09)	(0.35)	(1.34)
cons	-0.55	-0.75*	-0.95	-1.06**	-3.04*
	(0.29)	(0.25)	(0.62)	(0.24)	(1.19)
N	148	148	148	148	148
R^2	0.99	1.00	0.99	1.00	0.95
ECM					
Δlnw	-0.40***	-0.42***	-0.33*	-0.50***	-0.01
	(0.06)	(0.04)	(0.10)	(0.07)	(0.09)
ΔlnY	0.40***	0.42***	0.29**	0.44***	0.11
	(0.06)	(0.02)	(0.07)	(0.04)	(0.12)
Δepl	0.00	0.01	0.01	-0.00	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$\Delta \frac{I_{ICT}}{Y}$	0.15	1.25**	0.40	0.30	1.14*
	(0.46)	(0.34)	(0.46)	(0.23)	(0.41)
ΔRC	0.60	0.16	-1.30	-0.23	-0.45
	(1.28)	(1.07)	(1.26)	(2.28)	(3.09)
ϵ_{t-1}	-0.15**	-0.23**	-0.15***	-0.17***	-0.05
	(0.03)	(0.06)	(0.02)	(0.02)	(0.05)
cons	0.00	-0.01*	-0.01	-0.01	-0.02
	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)
N	132	132	132	132	132
R^2	0.46	0.67	0.47	0.58	0.23

***, **,*: statistically significant at 1, 5, 10 % level, respectively; robust standard error in brackets

Figure 23: The effect of wage on employment.

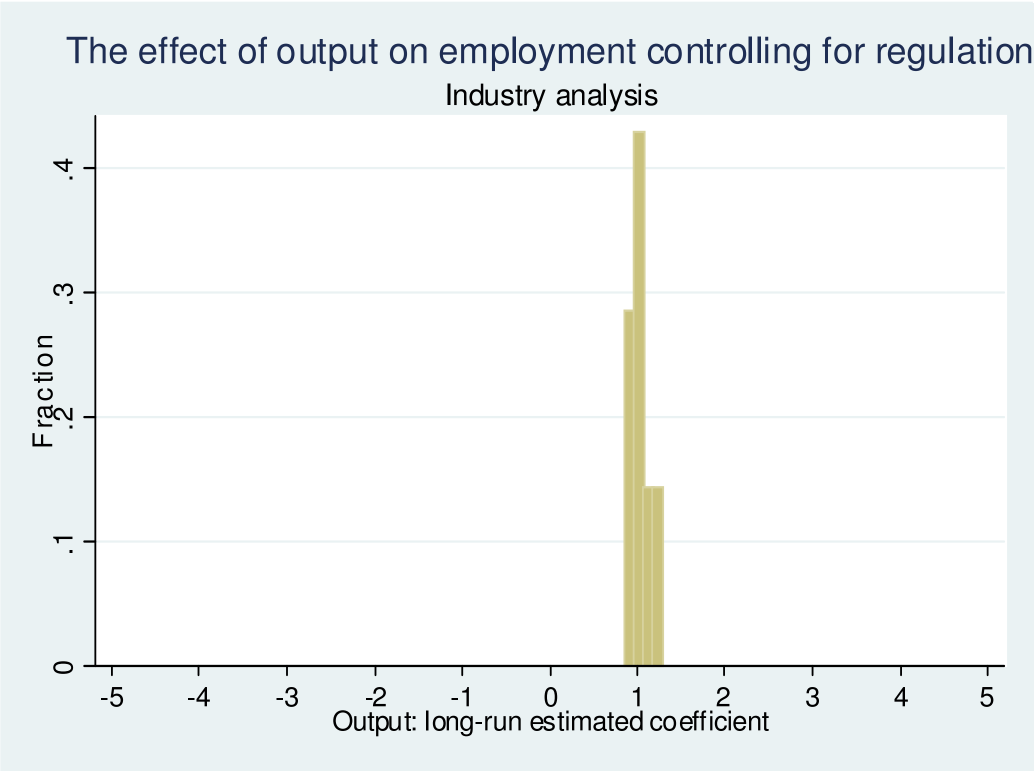

Figure 24: The effect of output on employment.

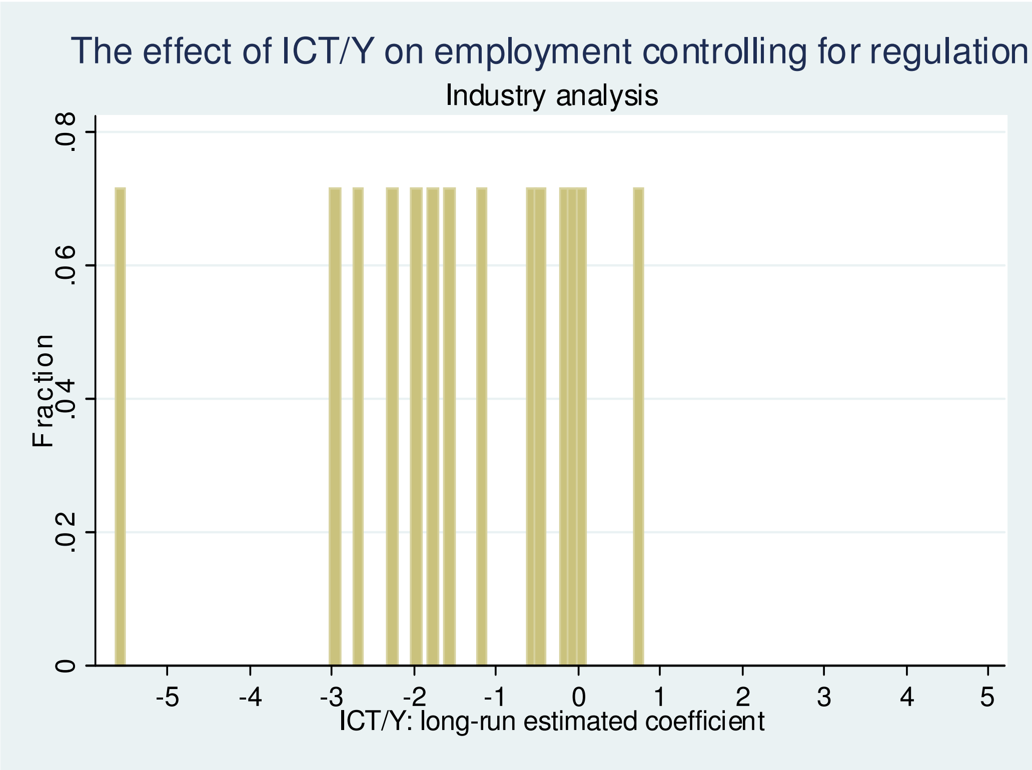

Figure 25: The effect of technology ($\frac{I_{ICT}}{Y}$) on employment.

Table 49: Non EU Countries , Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	AUS	JPN	KOR	USA
	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$
Long Run Regression				
lnw	-1.01**	-0.91**	-0.78***	-0.92***
	(0.35)	(0.31)	(0.20)	(0.21)
lnY	0.78***	0.89***	0.85***	0.79***
	(0.04)	(0.15)	(0.14)	(0.08)
ICT_TFP	1.90	1.04	1.14	1.78
	(1.61)	(1.46)	(1.88)	(1.25)
cons	-0.63	-0.99	-1.83	-0.36
	(1.45)	(1.41)	(1.14)	(0.67)
R^2	0.82	0.72	0.70	0.85
ECM				
Δlnw	-0.56**	-0.75	-1.01*	-0.24
	(0.19)	(0.39)	(0.44)	(0.37)
ΔlnY	0.78***	0.99***	0.98***	0.87***
	(0.11)	(0.06)	(0.09)	(0.05)
ΔICT_TFP	-0.03	-2.73**	-6.14***	-0.52
	(1.37)	(0.83)	(1.17)	(1.19)
ϵ_{t-1}	-1.03*	-1.00***	-1.02***	-1.02**
	(0.40)	(0.16)	(0.16)	(0.29)
cons	3.07***	9.12***	10.23***	3.13***
	(0.63)	(0.49)	(0.56)	(0.48)
N	625	625	625	625
R^2	0.78	0.88	0.77	0.84

***, **,*: statistically significant at 1, 5, 10 % level, respectively: robust standard error in brackets.

Table 50: Non EU Countries , Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	AUT	DNK	FIN	ITA	NLD	UK
	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$
Long Run Regression						
lnw	-0.38	-0.47	-0.51	-0.73***	-0.91**	-0.74***
	(0.44)	(0.27)	(0.35)	(0.17)	(0.25)	(0.14)
lnY	0.81***	0.79***	0.73***	0.57***	1.00***	0.93***
	(0.10)	(0.11)	(0.08)	(0.08)	(0.08)	(0.06)
ICT_TFP	-1.57	-0.96	-1.90	0.32	0.41	-0.96
	(1.37)	(1.80)	(1.59)	(1.13)	(1.35)	(0.86)
cons	0.64	-0.34	1.96	2.26**	-1.49	0.40
	(0.69)	(0.86)	(1.11)	(0.63)	(1.88)	(0.44)
R^2	0.72	0.72	0.71	0.75	0.68	0.84
ECM						
Δlnw	-0.86	-0.38	-0.15	-2.36**	-0.32	-0.46***
	(0.43)	(0.33)	(0.35)	(0.81)	(0.19)	(0.09)
ΔlnY	0.89***	0.80***	0.72***	0.72***	1.09***	1.09***
	(0.04)	(0.03)	(0.06)	(0.07)	(0.04)	(0.09)
ΔICT_TFP	-3.81***	-3.00***	-5.48***	-2.29	-0.34	-3.08***
	(0.36)	(0.58)	(0.67)	(1.12)	(0.73)	(0.18)
ϵ_{t-1}	-1.01***	-1.00***	-1.02***	-0.98**	-1.00***	-1.01***
	(0.18)	(0.09)	(0.22)	(0.27)	(0.05)	(0.17)
cons	3.44***	5.07***	2.59***	2.11***	4.59***	4.08***
	(0.21)	(0.15)	(0.26)	(0.53)	(0.21)	(0.57)
N	625	625	625	625	625	625
R^2	0.95	0.93	0.83	0.78	0.95	0.91

***, **,*: statistically significant at 1, 5, 10 % level, respectively: robust standard error in brackets.

Table 51: Non EU Countries , Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	AUT			DNK			FIN		
	$\beta/s.e.$ (1)	$\beta/s.e.$ (2)	$\beta/s.e.$ (3)	$\beta/s.e.$ (1)	$\beta/s.e.$ (2)	$\beta/s.e.$ (3)	$\beta/s.e.$ (1)	$\beta/s.e.$ (2)	$\beta/s.e.$ (3)
Long Run Regression									
lnw	-0.40	-1.19***	-1.13***	-0.48	-1.00***	-1.08***	-0.55	-0.99***	-1.03***
	(0.45)	(0.06)	(0.08)	(0.28)	(0.19)	(0.19)	(0.36)	(0.11)	(0.10)
lnY	0.82***	1.05***	1.07***	0.81***	1.03***	1.03***	0.74***	0.95***	0.95***
	(0.11)	(0.04)	(0.04)	(0.11)	(0.07)	(0.06)	(0.07)	(0.06)	(0.06)
ICT_TFP	-2.21	-1.34*	-3.38*	-0.63	-1.21*	-0.57	-3.45	-2.15	-3.01
	(2.50)	(0.46)	(1.26)	(2.28)	(0.50)	(0.71)	(2.27)	(1.13)	(1.54)
epl	-0.02		0.03	0.02		0.04	0.04		-0.00
	(0.04)		(0.03)	(0.02)		(0.02)	(0.03)		(0.02)
RC		-0.28	-0.30		-0.25	-0.25		-0.37**	-0.38*
		(0.16)	(0.17)		(0.13)	(0.12)		(0.11)	(0.13)
cons	1.37	1.41*	3.31*	-0.85	0.67	0.33	3.61*	2.19*	3.31*
	(1.37)	(0.49)	(1.22)	(1.31)	(1.24)	(0.97)	(1.66)	(0.93)	(1.46)
R^2	0.74	0.95	0.96	0.72	0.94	0.95	0.73	0.90	0.91
ECM									
Δlnw	-0.98	-1.12*	-0.70*	-0.44	-0.09	-0.24	-0.18	-0.20	-0.07
	(0.48)	(0.42)	(0.25)	(0.36)	(0.27)	(0.33)	(0.35)	(0.44)	(0.39)
ΔlnY	0.92***	1.10***	1.11***	0.81***	0.93***	0.93***	0.74***	0.70***	0.72***
	(0.03)	(0.10)	(0.08)	(0.03)	(0.07)	(0.07)	(0.05)	(0.06)	(0.07)
ΔICT_TFP	40.54***	-5.74***	83.06***	7.66**	-3.25**	5.38*	12.39**	-9.02***	22.06***
	(7.90)	(0.57)	(9.18)	(2.63)	(0.80)	(2.35)	(3.97)	(1.52)	(2.78)
Δepl	0.06***		0.16***	-0.01		-0.00	0.07**		0.05
	(0.01)		(0.03)	(0.01)		(0.01)	(0.02)		(0.03)
ϵ_{t-1}	-1.00***	-1.11**	-1.02**	-1.00***	-1.17*	-1.00***	-1.00	-1.17*	-1.07**
	(0.16)	(0.26)	(0.18)	(0.31)	(0.30)	(0.41)	(0.22)	(0.41)	(0.28)
ΔRC		-0.23**	-0.09		-0.10	-0.14*		-0.18*	-0.01
		(0.06)	(0.07)		(0.05)	(0.05)		(0.08)	(0.09)
R^2	0.96	0.85	0.93	0.94	0.89	0.89	0.85	0.66	0.71
N	550	350	308	550	350	308	550	350	308

***, **,*: statistically significant at 1, 5, 10 % level, respectively: robust standard error in brackets.

Table 52: Non EU Countries , Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	ITA			NLD			UK		
	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Long Run Regression									
lnw	-0.68**	-1.13***	-1.02***	-0.95**	-1.15***	-1.17***	-0.75***	-1.01***	-0.98***
	(0.19)	(0.08)	(0.09)	(0.26)	(0.12)	(0.16)	(0.14)	(0.09)	(0.10)
lnY	0.58***	1.05***	1.09***	0.99***	0.90***	0.91***	0.94***	1.07***	1.05***
	(0.09)	(0.06)	(0.06)	(0.07)	(0.08)	(0.08)	(0.06)	(0.04)	(0.03)
ICT_TFP	2.29	-1.27***	6.45*	3.00	-0.51	0.03	0.40	-0.12	1.88
	(3.94)	(0.24)	(2.29)	(2.96)	(0.83)	(2.84)	(0.92)	(0.57)	(1.07)
epl	-0.00		0.09***	-0.04		0.00	-0.03		-0.05
	(0.06)		(0.01)	(0.05)		(0.01)	(0.04)		(0.02)
RC		0.03	-0.10		0.05	0.03		-0.18	-0.17
		(0.09)	(0.09)		(0.17)	(0.18)		(0.24)	(0.24)
cons	-0.10	0.66	-8.81**	-4.09	1.43*	0.75	-1.13	-0.85	-3.01*
	(5.63)	(0.62)	(2.79)	(3.20)	(0.60)	(2.49)	(1.11)	(0.53)	(1.18)
R^2	0.77	0.95	0.96	0.72	0.91	0.91	0.85	0.95	0.95
ECM									
Δlnw	-2.47**	-1.53**	-1.11*	-0.48	0.41	0.36	-0.56***	-0.29	-0.75
	(0.80)	(0.44)	(0.44)	(0.29)	(0.60)	(0.61)	(0.10)	(0.52)	(0.35)
ΔlnY	0.73***	1.19***	1.18***	1.10***	0.96***	0.96***	1.11***	1.15***	1.09***
	(0.06)	(0.16)	(0.16)	(0.03)	(0.08)	(0.07)	(0.07)	(0.15)	(0.14)
$\Delta ICTTFP$	14.75	-5.31***	49.19***	2.68**	-4.55***	8.42***x	19.29***	-2.83***	23.75**
	(10.80)	(0.58)	(4.27)	(0.95)	(0.49)	(1.62)	(4.92)	(0.64)	(7.42)
Δepl	-0.02		-0.02*	-0.00		0.06*	0.05*		0.10
	(0.02)		(0.01)	(0.01)		(0.02)	(0.02)		(0.06)
ϵ_{t-1}	-0.95***	-0.95*	-0.99**	-1.00***	-1.00**	-1.00**	-1.02***	-0.97*	-0.86
	(0.24)	(0.32)	(0.26)	(0.06)	(0.26)	(0.26)	(0.16)	(0.43)	(0.44)
ΔRC		0.10**	0.03		-0.07	-0.01		-0.14*	0.02
		(0.03)	(0.03)		(0.06)	(0.11)		(0.06)	(0.05)
cons	2.20***	5.06***	4.97***	4.71***	3.65***	3.65***	4.23***	4.42***	4.04***
	(0.43)	(1.00)	(0.97)	(0.21)	(0.44)	(0.39)	(0.49)	(0.96)	(0.89)
N	550	350	308	550	350	308	550	350	308
R^2	0.83	0.83	0.86	0.95	0.80	0.81	0.93	0.77	0.81

Table 53: EU Countries (1st Part), Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	AUT	DNK	FIN	GER
	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$
Long Run Regression				
$\ln w$	-1.13***	-1.12***	-1.14***	-1.13***
	(0.09)	(0.18)	(0.06)	(0.11)
$\ln Y$	1.06***	1.02***	0.95***	1.10***
	(0.04)	(0.06)	(0.06)	(0.05)
RC	-0.35*	-0.17	-0.36**	-0.16
	(0.16)	(0.11)	(0.11)	(0.26)
epl	0.03	0.07*	-0.07*	-0.04**
	(0.02)	(0.03)	(0.03)	(0.01)
$ICT\ TFP * RC$	3.97	-7.94	-20.60*	-87.59*
	(31.29)	(4.96)	(9.11)	(33.50)
$ICT\ TFP$	-23.51**	2.48	3.13	30.45*
	(7.10)	(1.38)	(2.78)	(10.49)
cons	-0.44	-0.09	0.43	-0.71
	(0.43)	(1.11)	(0.43)	(0.46)
ECM				
$\Delta \ln w$	-1.25**	-0.22	-0.19	-0.41
	(0.36)	(0.30)	(0.37)	(0.22)
$\Delta \ln Y$	1.13***	0.97***	0.73***	1.23***
	(0.09)	(0.07)	(0.08)	(0.10)
ΔRC	-5.23*	-2.66	-2.25	-1.09
	(1.99)	(1.48)	(2.02)	(0.97)
Δepl	-0.14***	0.08**	0.17**	-0.02*
	(0.03)	(0.02)	(0.05)	(0.01)
$\Delta ICT\ TFP$	-55.15***	0.81	19.74***	25.75***
	(7.29)	(0.68)	(3.71)	(4.80)
$\Delta\,(ICT\ TFP * RC)$	39.91	-5.75*	-52.52*	-80.99***
	(20.65)	(2.35)	(18.82)	(19.01)
$\hat{\epsilon}_{t-1}$	-1.01**	-0.99**	-1.01**	-0.98**
	(0.26)	(0.31)	(0.29)	(0.28)
cons	4.42***	5.67***	2.64***	5.36***
	(0.39)	(0.30)	(0.34)	(0.73)
N	294	294	294	294.
R^2	0.88	0.90	0.71	0.85

***, **,*: statistically significant at 1, 5, 10 % level, respectively: robust standard error in brackets.

Table 54: EU Countries (2nd Part), Dependent Variables: lnN in the L.R. Regression, ΔlnN in the ECM

	ITA	NLD	SWE	UK
	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$	$\beta/s.e.$
Long Run Regression				
$\ln w$	-1.08***	-1.17***	-0.99***	-0.96***
	(0.09)	(0.15)	(0.18)	(0.10)
$\ln Y$	1.08***	0.92***	0.91***	1.05***
	(0.06)	(0.08)	(0.07)	(0.04)
RC	-0.04	0.01	-0.07	-0.15
	(0.10)	(0.16)	(0.07)	(0.32)
epl	0.05**	-0.00	0.00	0.02
	(0.01)	(0.03)	(0.00)	(0.05)
$ICT\ TFP * RC$	-34.01**	6.69	-0.25	-7.30
	(10.50)	(8.17)	(34.35)	(21.14)
$ICT\ TFP$	3.07	-2.79	-10.51	-4.40
	(3.61)	(2.41)	(5.10)	(3.31)
cons	-1.38*	0.78	0.46	-0.97*
	(0.48)	(0.74)	(0.81)	(0.38)
ECM				
$\Delta \ln w$	-1.66**	0.17	0.75	-0.67
	(0.40)	(0.57)	(0.93)	(0.45)
$\Delta \ln Y$	1.23***	0.97***	0.89***	1.13***
	(0.13)	(0.07)	(0.04)	(0.13)
ΔRC	-7.39***	-2.02	-0.20	-5.38**
	(1.69)	(1.05)	(0.57)	(1.47)
Δepl	-0.13***	0.06	0.00	0.41**
	(0.02)	(0.03)	(0.00)	(0.14)
$\Delta ICT\ TFP$	-16.87***	7.46*	8.15	-6.67**
	(3.24)	(2.77)	(6.23)	(2.11)
$\Delta\,(ICT\ TFP * RC)$	-5.43	-6.30	-68.02*	3.59
	(4.95)	(7.11)	(26.97)	(6.24)
$\hat{\epsilon}_{t-1}$	-0.86*	-1.01**	-1.05**	-1.01*
	(0.29)	(0.29)	(0.31)	(0.46)
cons	5.22***	3.70***	5.42***	4.23***
	(0.81)	(0.40)	(0.19)	(0.84)
N	294	294	294	294
R^2	0.88	0.83	0.78	0.80

***, **,*: statistically significant at 1, 5, 10 % level, respectively: robust standard error in brackets.