THREE ESSAYS ON WAGES AND PRODUCTIVITY

by Mariann Rigó

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Supervisor: Prof. John S. Earle

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DEPARTMENT OF ECONOMICS

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Advisor:____John Earle

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Mariann Rigó

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ABSTRACT

The recent availability of linked employer – employee databases (LEED) opened up new opportunities for empirical labor research. Among the variety of areas in which the LEED can potentially be utilized, my thesis examines earning regressions and production functions supplemented with information on both the employers and the employees. Wage regressions based on LEED may control for – besides the individual level variables, such as age, gender, education, occupation – various firm-level variables. Production functions including traditionally only firm level variables, such as the capital and the labor input, may be augmented with the worker composition of the firm offering the opportunity to study e.g. the relative productivity of various employee groups.

The first chapter of the thesis utilizes the rich firm-level and employee information of the LEED to investigate the wage differential associated with the conclusion of firm-level collective contracts. The historical roots of the Hungarian trade unions are in a sharp contrast with the origins of the industrial relations system in Western European or Anglo-Saxon countries. After the regime change, trade unions in the transitional countries had to reorganize themselves, find their new roles in the fundamentally changed economic environment, and cope with their social inheritance. The outcome was a decentralized structure, where the firm-level trade unions are the most important channel of collective negotiations. The estimation results mostly reflect this fragmented industrial relations system, and imply that the wage advantage associated with firm-level agreements is tiny. I estimate numerous regression specifications varying the scope of the explanatory variables (individual-level and firm-level controls, firm fixed effects), and the level of aggregation (firm-level vs. individual-level). In line with previous results, the study finds that the largest portion of the raw wage gap is explained by observable firm-level variables. The 26 percent raw wage gap estimated on individual-level data decreases to 6 percent after controlling for individual and firm-level characteristics, and to 2 percent when including time invariant firm-level unobservables. On the other hand, firm-level regressions using an accounting measure, the total wage bill of the firm as the dependent variable, suggest a surprisingly high wage gap of 8 percent in the final specification.

Chapter 2 and 3 pursue a different path, and – building on the rich employee and employer information of the LEED – investigate production functions in the way pioneered by Hellerstein and Neumark (1999). In Chapter 2 (joint with Anna Lovász) we examine the

long-term adjustment process following the sudden devaluation of certain labor market skills due to the technological and organizational changes brought about by the regime change. Our hypothesizes are based on the model of skill obsolescence and imply that (a) the devaluation of skills should affect highly educated older workers more severely (b) the disadvantage should disappear over time as newer cohorts acquire more suitable human capital, and (c) the timing should differ among firm ownership types, reflecting the inflow of modern technologies and practices. Rather than focusing on wage differentials, we estimate the firm-level productive contribution of older relative to younger workers differentiated by education level. To assess long-run trends, we adapt the augmented production function methodology and apply it to the Hungarian LEED covering from before (1986) to 20 years after (2008) the economic transition. The results suggest that - in line with the model - the within firm productivity differential between older and younger workers following the transition was largest among the highly skilled (-0.13 in 1996-2000). The fall in relative productivity followed the inflow of modern capital: the gap was largest in 1992-1995 in foreign-owned firms (-0.6), while it appeared later in domestic firms (-0.18 in 1996-2000) before disappearing by 2006. Our results based on within-firm estimates are indicative that the speed of adaptation of older workers to modern technology was probably faster than implied by cross-sectional OLS estimates. By the last period, roughly fifteen years after the transition, the old – young relative productivity coefficients are comparable to those found in studies on Western European and U.S. data, documenting an insignificant or small decrease in productivity for older age groups.

Chapter 3, also based on the worker composition augmented production function methodology, aims to give a more detailed picture of the relationship between age and productivity. Ageing is a particularly relevant research question in Hungary, where both the demographic trends and the low employment rate of the older worker groups make it difficult to cope with the increasing economic burdens of an ageing society. From the firms' point of view, a crucial element of the problem relates to how the productivity of employees changes as they grow older. The current paper addresses this issue by analyzing the connection between the age composition of firms and their productivity, grouping workers into detailed age intervals, and using the most recent econometric techniques to handle the unobserved firm heterogeneity and simultaneity issues. Among the variety of methods, structural approaches by Levinsohn and Petrin (2003) and Ackerberg, Caves and Frazer (2006) are also presented. The results on the pooled sample (covering the years 1992-2008) are suggestive that older workers are less productive. Estimates in the within dimension document that productivity drops significantly at the ages of 35, 45, and 55. The results imply that increasing the share of workers below 35 by 1 percentage point (relative to workers aged 35-45) increases value added by 0.6 – 0.7 percent. The similar estimates for employees aged 45-55 lie in the range of -0.12 – -0.1, while the estimates for workers aged over 55 are in the range of -0.2 – -0.17. However, splitting the panel into two samples (before and after 2000) reveals that the productivity disadvantage of older employees disappears in the second period, and methods taking care of both the unobserved heterogeneity and simultaneity issues indicate an essentially flat age – productivity profile in that period. Therefore, the Hungarian results covering the most recent years do not confirm the usual skepticism over the negative impact of the ageing population on firms' productivity. The estimates covering the years after 2000 are in line with the results obtained in Chapter 2 documenting insignificant productivity gap between older and younger employees (both in the skilled and unskilled groups) in the most recent years.

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CHAPTER 1

1 Estimating Union – Non-union Wage Differential in Hungary

1.1 Introduction

Social dialogue, improving the working and employment conditions based on a collective representation of employees, is an essential element of EU policy. Social dialogue is not only the right of EU citizens, defined in the Community acquis, but it is also a tool to implement certain policy elements[1] (Ladó et al, 2003). While continental Western European countries have traditionally strong social partners exercising their bargaining activity both at firm, sectoral and national level, and reaching a bargaining coverage of close to 100 percent, social dialogue in transitional countries is a fragile institution showing a fragmented structure, and covering only a fraction of the workforce. The large discrepancy between the Western and the transitional countries is not surprising knowing the different historical roots of the social partners. While trade unions in Western Europe inherited their attitudes from the Taylorist and Fordist, and later from the Japanese style organization paradigm[2] (Tóth, 2006b), trade unions in the transitional countries had to reorganize themselves, find their new roles in the fundamentally changed economic environment and cope with their social inheritance. The outcome in most transitional countries was an industrial relations system where the firm level is the most (and only)

[1] For example, the Amsterdam Treaty stipulates that Community directives can be implemented at the national level by agreement between social partners rather than by legislation.

[2] In the 50s and 60s, in the Taylorist and Fordist work organizations collective agreements limited employers' flexibility regarding wages and employment conditions to the smallest possible (e.g. rigid wage scale system, exact regulation of fringe benefits, system of job description specifying exactly the content of each job). Starting from the 80s, the Japanese style organization paradigm replaced the earlier rigid institution leaving some flexibility for the employer e.g. to reward employees by individual performance. The power of collective agreements was limited afterwards to maintain a minimum solidarity between employees and to restrict the flexibility of local bargaining (Tóth 2006b).

important channel of collective negotiations. Compared to continental Western Europe where sectoral agreements essentially cover the whole economy, the industrial layer is the least developed one in transitional countries. Also opposite to the Western practice, agreements on the national tripartite forum made by the employers', employees' associations and the government, are not binding[3]. Trade union confederations at the national level act only as a consultative body.

Though unionization is one of the most heavily studied topics in Anglo-Saxon countries and in continental Western Europe, little is known about the nature of industrial relations in transitional countries.

While descriptive and case studies[4] yield us a detailed picture into the process of how social partners reorganized themselves after the regime change, and a few surveys[5] have been also carried out giving some insight into the attitude of social partners, there are almost no studies quantifying the labor market impact of unionism in these countries (for exceptions, see Neumann 2001, Kertesi and Köllő 2003, Iga et al 2009). Based on case studies and small-sample surveys, researchers share the opinion that collective bargaining is weak in transitional countries, and unionism has little or small labor market impact. One

[3] Continental Western European countries have a tradition of national bilateral bargaining, which might lead to binding agreements (Ladó et al, 2003).

[4] The In Focus chapter of The Hungarian Labour Market, Review and Analysis 2006 (edited by Károly Fazekas and Jenő Koltay) gives a comprehensive overview of the Hungarian industrial relations. For example, the studies by Tóth (2006 a) and Neumann (2006 a and b) provide a detailed picture of the the employers' organizations and trade unions, describe the process of reorganization of these institutions after the regime change, and emphasize their current strenghts and weaknesses. Tóth (2006 b) analyzes the different characteristics and attitudes of post-guild (Western European) and post-socialist trade unions and offers possible explanations for the fragmented structure and weak power of trade unions. The Ministry of Social Affairs and Labour, being responsible for the collection and management of data on collective agreements, publishes on its home page (http://www.szmm.gov.hu/mkir/kszelemzesek.php) case studies of special industries describing the actors of industrial relations and analyzing the content of collective agreements. A country-wide comprehensive study based on the industrial case studies is Fodor, Nacsa and Neumann (2008).

Regarding the experiences of other transitional countries, Pollert (1999) provides a short overview of industrial relations during the transition in Poland, Hungary, Slovakia and the Czech Republic. The East German and the Hungarian experiences are compared in Frege and Tóth (1999). Ladó and Vaughan-Whitehead (2003) discusses the industrial relations systems in the framework of the EU social policy of the ten countries that joined the EU in 2004.

[5] For example, the survey study of Frege and Tóth (1999) covers the Hungarian and east German clothing industry and examines the extent of union solidarity in these two countries. Pollert (1999) presents survey evidence of union members' experience of workplace change and trade union activity in the Czech Republic.

aim of the paper is to revisit the assumed weak role of trade unions in these countries by quantifying the wage impact of collective agreements based on a Hungarian large representative linked employer-employee panel data, which covers the transitional period as well as the years around the EU accession.

The other contribution of the paper is related to the methodology. Early studies on the union wage gap were based on individual household surveys, and included mostly human capital controls into their wage regression analysis[6]. However, recent papers using linked employer-employee data (e.g. Card and de la Rica 2006, Gürtzgen 2006) and enterprise-level studies (DiNardo and Lee 2004, Lalonde, Marschke and Troske 1996, Freeman and Kleiner 1990) called the attention for the important role of firm-level observable and unobservable controls in the wage regression. Due to the unique nature of the dataset, I am able to include into the analysis a rich number of employee and employer characteristics as well as firm fixed effects. This was not possible in any of the earlier studies on transitional countries, and the empirical evidence on the extent of union wage gap, after taking into account firm-level unobservables, is rather limited in other countries as well.

Besides, the Hungarian data offer a unique opportunity to analyze if the *content* of the collective agreement has an important impact on the wage gap. I have separate information on the number of collective agreements, and on the number of wage agreements. In Hungary, wage agreements constitute a subset of collective agreements, which include wage regulations. Roughly one-third of the agreement records refers to agreements without wage regulations. A priori it is unclear if effectively binding firm-level wage agreements, or already the mere presence of an organized union at the firm assures

[6] For an excellent survey of these papers, see for example, Lewis (1986) and Blanchflower and Bryson (2004).

higher wages. None of the previous studies used separate collective and wage agreement records for the analysis.

Furthermore, the study contributes to the debate regarding the proper level of aggregation as the analysis will be carried out both on individual and firm level data. Enterprise-level studies from the US (e.g. DiNardo and Lee 2004) estimate smaller wage impacts than individual-level analyses. However, using linked employer-employee data, and analogous variables in both the individual and firm-level estimations, estimates should be identical (Card and de la Rica 2006). As the Hungarian contract variable is defined at the level of the firm, the exercise of providing estimates both at the level of individual and at the level of firm, seems a natural one. Besides, the Hungarian data provide two types of dependent variables at the firm level. The first one comes from the aggregation of individual wages, and the second one is the total wage bill of the firm, an accounting measure. The current paper is, to my knowledge, the first study to provide estimates both on individual and firm level using various wage measures.

The results suggest that firm-level contracting is associated with 1.2 – 8.2 percent higher wages depending on specification. Using individuals' wages as the outcome measure, the average wage gap is 2.2 – 3 percent, and changes only slightly if estimation is carried out at the individual or at the firm level. Nevertheless, using the firm-level wage bill as the dependent variable, the wage gap is larger, on the order of 6-8 percent. The experiments with the collective agreement and the wage agreement variables confirm that, though wage agreements secure slightly higher wages than only collective agreements, the mere presence of an organized union at the firm, which is able to conclude collective contract, is enough to secure higher wages.

The paper is organized as follows. Section 1.2 provides some background on the institutional structure of industrial relations in Hungary in comparison to the Anglo-Saxon and other continental European systems. Section 1.3 describes the data used in the estimation including summary statistics. Section 1.4 discusses the methodology, and results are presented in Section 1.5. Section 1.6 concludes.

1.2 Institutional Setting

The Hungarian institutional setting can be characterized as a heavily decentralized system where bargaining at the firm level – individual and collective bargaining – are the most important channels of the wage negotiations. Sectoral collective agreements are almost absent, and even if present, they are weak regarding their regulatory power[7]. Besides the firm-level layer, union confederations at the national level are also able to influence the bargaining outcomes through their participation on the tripartite forum. Parties of the tripartite forum, called as the National Interest Reconciliation Council, representing trade union confederations, employers' associations[8] and the government issue recommendations for the minimum wage and for the annual wage increase, which

[7] According to industrial case studies, firm managers insist on having large autonomy in determining wages and conditions of work. Thus, sectoral agreements usually set very low requirements, which are easy to meet. The reluctance of companies to engage in sectoral agreements is mirrored by the situation that most of the employers' organizations are not entitled to sign sectoral agreements, and even if signed, they specify "opt-out" clauses concerning the most restrictive stipulations. This situation results in sectoral agreements being nothing else than a "collection of good wishes" (Neumann 2006b, p129).
An important reason behind the weak performance of higher level (sectoral and confederate) unions is their poor financial situation, the lack of specialized staffs and experts. Trade unions at this level hardly employed any fresh graduates since they were set up, and tend to operate with only few staff members not being enough to fulfill the interest representation role. In principle, firm-level trade unions should pay 40 to 60 percent of their fees to higher level unions. However, the actual transfers are much smaller reflecting the large autonomy of firm-level trade unions, which they gained during the transition (Neumann, 2006 a).
Regarding the coverage of industrial agreements, before 2005, the first and only wave of sectoral negotiations took place in 1992. The next wave occurred in 2005 when industry level agreements were signed in the construction and in the private security industries. In 2001, the share of employees covered by a sectoral agreement was 5.9 percent, which is quite low compared to the coverage rate of 37.2 percent in case of the single employer contracts (Neumann, 2006 b, Table 11.8.).
[8] Currently there are six large union confederations and nine employers' associations. These national level institutions and the government takes part in the National Interest Reconciliation Council.

serve as a guideline for the firm-level collective negotiations. However, agreements made at this level are not binding, unless by a governmental decree[9].

Workers at the company level are represented by two institutions: works councils and trade unions. Works councils were set up by the Labour Code in 1992 to introduce a new form of employee representation, which is independent of union membership. The aim was to create an institution, which is close to the German model where works councils operate as a platform for joint decisions in the most important questions by the workers and managers. However, the co-determination rights in the Hungarian version were limited to the use of the social fund; otherwise, they were only given information and consultation rights. Moreover, the two institutions often overlap in Hungary having the same people in the works council's and trade union's seats. As the bargaining right of unions depends on the number of votes they get in the works councils, union members have strong incentives to ensure seats for their nominees in the works councils. Thus, works councils are mostly regarded as useless and unnecessary institutions without any functional role (Benyó et al, 2006).

Bargaining at the firm level takes place through individual bargaining and by concluding collective contracts. Traditionally, even in the socialist era, individual bargaining has been a more dominant channel of wage bargaining than firm-level collective agreements[10]. Before the regime change, collective agreements basically served as an "implementation manual of the Labour Code" (Tóth 2006b, p 152), and the role of

[9] According to the Labour Code (1992, Act XXII., paragraphs 17 and 144), the minimum wage is decided by the government after consulting with the employers' and employees' representatives at the National Interest Reconciliation Council. Ideally, the parties of the tripartite forum should jointly agree on the minimum wage, which is then accepted by the government. However, lack of joint agreement, the government can unilaterally decide on the extent of minimum wage. Except for 2001, when the representatives of employers and employees could not decide on the extent of minimum wage, which was then decided by the government, in each year the minimum wage was a joint agreement of the parties at the National Interest Reconciliation Council.

[10] Wages during the socialism were regulated by the Labour Code. However, actual wages were allocated from an enterprise wage fund, and managers had a wide range of flexibility to decide on individual wages (Pollert 1999, Tóth 2006b).

labor unions was limited to provide recreation, housing and holiday services for their members. However, even after 1990, when trade unions reorganized themselves and became voluntary associations, trade union activity was largely affected by the social inheritance, and collective agreements, instead of representing the collective voice and the automatic solidarity between the employees, mostly aimed only to lay down framework conditions, and ensured considerable flexibility for the employers to decide on individually bargained wages (Tóth 2006b). The survey analysis by Frege and Tóth (1999) documents a weak union solidarity among Hungarians using a sample of firms in the clothing industry, and attributes the lack of confidence in the union institutions to the fragmented interest representation system: works councils without any functionality and decisive role in the firms' employment policies and weak bargaining power of decentralized firm-level trade unions[11].

In spite of the apparent weaknesses of the firm-level trade unions, these institutions constitute the only alternative to engage in collective wage bargaining and regulate the employment and working conditions with unified power. As such, firm-level trade unions constitute an important level of industrial relations in Hungary[12].

Firm – level trade unions have the privilege by law to engage in collective bargaining and to conclude agreements[13]. Once concluded, the agreement is automatically extended to all employees of the firm. While collective agreements in the Anglo-Saxon countries and in Western Continental Europe include precise and strict regulations

[11] The authors found a more supporting attitude towards unions in East Germany, where works councils are based on the concept of co-determination, and workers and entrepreneurs decide jointly in vital decisions in the company. Thus, even if trade unions are not successful in collective bargaining, the strong statutory right of the works council provide a minimum interest representation for the workers.

[12] The situation is similar in the Czech Republic and Poland with the decentralized firm-level bargaining being basically the only source of collective negotiations. In Slovakia, sectoral agreements are more important, and covered more than 50 percent of the workforce in 2001 (Lado and Vaugham-Whitehead 2003, Table 1). The other exception is Slovenia where the coverage rate of sectoral agreements were close to 100 percent in 2000 (Lado and Vaugham-Whitehead 2003, Table 1).

[13] As regulated by the Labour Code (1992, Act XXII, paragraph 33), trade unions have the right to engage in collective bargaining after winning more than 50 percent of the votes at the works council elections.

concerning wages, the Hungarian collective agreements have mostly vague regulations on wage elements. Moreover, one third of the regulations do not even include any stipulations on wages. Collective agreements including regulations on wages are termed separately as wage agreements[14]. While wage agreements are negotiated on a yearly basis, collective agreements are often contracts of indefinite duration[15].

Based on a recent study analyzing 304 collective agreements in 20 industries[16], the content of the Hungarian collective agreements share the following main features. They usually reflect an interest representation attitude inherited from the socialist era: leave considerable autonomy for the management to decide on individual wages in order to avoid conflicts and to ensure the survival of the trade union. Most of the agreements include precise regulations on extra working hours, overtime work, non-wage and social benefits. These areas were traditionally well-regulated in pre-transition collective contracts as well. Nonetheless, regulations on wage elements are vague specifying mostly only guaranteed wages[17] and formulating target wage recommendations. The elements of modern HR techniques (e.g. the specifications of performance pay, group bonuses) are almost missing from the agreements[18].

The coverage of agreements varies substantially by the size of the firm, by industry, and also shows some variation over time. Collective agreements are more likely to be

[14] Though the Labour Code does not explicitly use the term wage agreement, wage agreements have the same legal status as collective agreements. In practice, it is a separate part of the collective agreement, which is updated annually (Neumann 2006b). By definition, wage agreements are a subset of collective agreements.

[15] The data of wage and collective agreements are recorded by the Ministry of Social Affairs and Labour. If not specified otherwise, the duration of wage agreements is assumed to be a year, while most of the collective agreements have indefinite duration. However, the Ministry is actively monitoring the validity of the contracts and modifies the records accordingly. For more details on the agreement records and cleaning issues, see the Data section.

[16] The study was ordered by the Ministry of Social Affairs and Labour in 2006 and 2007. Case studies analyzed the text of 304 collective agreements in 20 industries, and the main findings were summarized by country-wide a comprehensive study (Fodor – Nacsa – Neumann 2008). All the case studies and the summary paper are available on the ministry's webpage (http://www.szmm.gov.hu/mkir/kszelemzesek.php).

[17] Guaranteed minimum wages constitue part of the collective contracts in firms where wages explicitly depend on the performance of the employee. The guaranteed wage is usually the base salary or a certain fraction, usually 70-80 percent of the base salary.

[18] There are a few exceptions in the chemical industry with collective agreements defining both the bonus-tasks and the allocation of bonuses.

concluded in large companies. For example, in 2004, only 9.4 percent of companies employing less than 50 employees concluded wage agreement, while the coverage was larger than 50 percent in companies with more than 300 employees (Neumann 2006, Table 11.16.). By industry, the mining, transport, and the electricity industry were the most covered sectors with a coverage rate of around 80 percent, while in construction, trade and financial intermediation the share of covered employees was around 25 percent (Neumann 2006, Table 11.15.). Over time, the number of registered collective agreements does not show substantial variation ranging between 1200 and 1300 reported agreements in the period 1998 – 2004 (Neumann 2006, Table 11.3.). On the other hand, the number of registered wage agreements decreased from around 800 in 1998 to 515 reported cases in 2004. The drop in the number of wage agreements in recent years is due to the growing influence of the national level regulations in the wage determination. Starting from 2001, the statutory minimum wage increased substantially, reaching higher values than the firm-level trade unions hoped for[19] . As a consequence, the number of agreements specifying higher wage increases than the national one dropped substantially[20].

Comparing the institutional setting to other countries, industrial relations in Hungary can be characterized as being a mixture of the two main regime types, the Anglo-Saxon and the continental European ones, but being closer to the decentralized Anglo-Saxon regime. Similarly to the US and UK, the main level of bargaining is the firm, and since industrial agreements are rare and lack an effective extension mechanism, the two most important sectors of the economy are those covered by a firm-level agreement and the

[19] The statutory minimum wage increased by 60 percent in 2001 compared to its level in 2000. Starting from 2006, the government introduced a three-tier minimum wage system in which the guaranteed minimum wages differ by education (a universal minimum wage, two compulsory higher levels for skilled workers and an even higher level for university graduates). Due to these regulations, the number of wage agreements dropped significantly in recent years, especially after 2005. According to the ministry's records, the number of reported wage agreements dropped to 267 in 2007 and further to 185 in 2009.

[20] Despite the increase of minimum wage, there would be scope for wage agreements to regulate other aspects of the salary system. However, as case studies underpin (e.g. Fodor, Nacsa, Neumann 2008), wage agreements in most cases restrict themselves to specifying minimum and guaranteed wages and average wage increases.

uncovered one[21]. On the other hand, the dominant dimension of industrial relations in the Western European continental countries (e.g. in Spain, Italy, the Netherlands, Portugal) consists of a network of sectoral agreements, which are practically extended to all firms in the economy. Firm-level agreements may coexist with industrial agreements (e.g. Spain, Portugal, the Netherlands) or be an alternative to them (e.g. Germany), but these firm-level contracts cover much smaller fraction of the workforce[22]. Despite the relatively high degree of centralization of industrial relations compared to the US and the transitional countries, there are substantial differences between the continental Western European regimes. Since Calmfors and Driffill (1988) much attention has been paid to the centralization and the coordination dimensions of the regimes[23]. According to the Calmfors – Driffill hypothesis, bargained wages are the highest and macroeconomic outcomes are the worst under intermediate degrees of centralization, which in most cases refers to sectoral bargaining. On the other hand, both decentralized and centralized bargaining produce lower wages and better macroeconomic outcomes[24]. However, in many countries (e.g. Portugal, the Netherlands) there are multiple-level bargaining with coexisting

[21] Note, however, that there are important differences in the historical backgrounds of trade unions in the Anglo-Saxon and transitional countries. Additionally, the process of negotiation, and the relevance of individual membership (whether individual-level or firm-level coverage is relevant) is different.

[22] For example, in Spain, 15 percent of workers were covered by firm-specific contracts in 1991 (Card and de la Rica, 2006), and in Portugal, the coverage of firm-specific contracts was less than 10 percent in 2000 (Cardoso and Portugal, 2005).

[23] The term centralization usually refers to the highest level at which negotiation takes place, while coordination refers to some form of synchronization or information exchange between the bargaining units. Other authors differentiated between countries by the extent of corporatism, which comprises various factors, such as the centralization, coordination within national-level associations, political and ideological consensus, existence of tripartite negotiations. The concept of corporatism is not a well-defined term. For example, Hartog et al (2002, p 318) defines corporatism as “a structure of well-organized interaction and consultation between union federations, employer federations, and the national government on all issues of social economic policies, including labour legislation and social protection”. For more examples, see Calmfors and Driffill (1988), page 24.

[24] When the bargaining is decentralized, which usually corresponds to enterprise level bargaining, unions’ wage demands are suppressed by market forces (unable to increase firm’s cost level above that of competitors), while under centralized bargaining the wage demands are mitigated by internalizing the various negative externalities (e.g. consumer price, input price, unemployment externalities). The authors pointed out that the crucial factor is not the level where negotiation takes place, but the level at which coordination occurs. In their interpretation, centralization is “the extent of inter-union and inter-employer cooperation in wage bargaining with the other side” (Calmfors and Driffill, 1988, p 17). On the other hand, Bruno and Sachs (1985) hypothesize a monotonic relationship between the degree of corporatism and real wage moderation with more corporatist countries having lower wages.

bargaining arrangements, and there is no theory to give guidance in such cases. Thus, the relationship between the wage outcomes and the characteristics of the institutional setting is a priori not clear, and probably depends on many features of the institutional setting.

According to the ranking of Calmfors and Driffill (1988), Austria, Norway and Sweden are the most centralized countries, and UK, US and Canada are at the other extreme of the scale, while Germany and the Netherlands lie in between. Ranking the countries by the extent of corporatism (Bruno and Sachs, 1985), Germany and the Netherlands are also considered to be highly corporatist countries among Austria, Norway and Sweden. According to the OECD's ranking (OECD 2004) covering the period of 1995-2000, Norway is the most centralized country with the highest level of coordination, followed by Portugal with similarly high centralization and coordination scores. Austria, Germany and the Netherlands are considered to be medium centralized countries with predominantly industry-level bargaining and high level of coordination. Spain and Sweden are medium centralized with medium degree of coordination, while Italy is considered to be decentralized with high degree of coordination. Transitional countries lie at the low end of both the centralization and the coordination scale[25]: fragmented firm-level contracts are the most important channel of collective negotiations, and the thin layer of sectoral agreements cover only a fraction of the employees. Due to the small coverage of industrial agreements and their weak regulatory power documented by previous studies (e.g. Tóth 2006b), I only investigate the wage impact of the firm-level collective contracts in Hungary. Thus, the results presented in the paper are, from one point of view, comparable to the findings in Anglo-Saxon countries analyzing the wage impact of the covered sector (by firm-level contracts) relative to the uncovered one.

[25] An exception is Slovakia, which is classified as having a modestly centralized and coordinated institutional structure due to the more important role of sectoral agreements (OECD Employment Outlook, 2004, p 151. Table 3.5.)

The empirical findings of the few quantitative studies from the transitional countries are in line with the conclusions of the survey and case studies presented above, and document modest or statistically insignificant wage impacts. Neumann (2001) using Hungarian data from 1998 finds a statistically significant wage impact of 5.6 percent in case of firm-level collective agreements. Kertesi and Köllő (2003) analyzing the interaction of market concentration and unionization on the same dataset from 1998 concludes that high wages in certain industries are the result of industrial rents in concentrated sectors, which are then grabbed by unions. Their estimates on the magnitude of the wage impact of collective agreements are similar to the one obtained by Neumann (2001). Iga et al (2009) uses three transitional datasets, Hungarian and Czech data from 2002 and Polish data from 2004 to estimate the impact of firm-level and industry-level collective agreements. On average, using the cross-sectional data, they do not find a significant wage impact in either of the countries. In Hungary, firm-level collective agreements are found to be associated with higher wages on the order of 5-7 percent in those firms, which were set up prior or a few years after the transition. The Czech and Polish data showed large and significant wage premium in those firms, which were set up after 1996[26]. The magnitude of the wage gain in these late-transition firms was around 18 percent using the Czech, and 8-9 percent using the Polish data. Industrial agreements were not found to have significant impact in either of the countries[27].

Thus, quantitative results of transitional countries show, on average, a small or insignificant wage impact of collective agreements, in line with conclusions from case studies and survey analyses. These results on average wages are comparable in magnitude

[26]The fraction of late-transition firms is 2.87 percent and 18.87 percent in the Czech and Polish data, respectively (Iga et al, 2009, Table 4.). A somewhat odd result is a negative wage gap of firm-level collective contracts of around 10 percent in early- transition firms using the Czech data.

[27] The estimates by the workers' skill group showed that the Czech and the Polish wage premium in late-transition firms is concentrated among the medium- and high-skill workers, and industrial agreements are associated with higher wages among the low-skilled in the Czech Republic. In Hungary, the wage premium was roughly evenly distributed among the skill groups, and industrial agreements increased the low-skilled wages in early-transition firms.

to the empirical findings from continental Western European countries, see for example Hartog el al (2002) on Dutch data, Card and de la Rica (2006) on Spain, or Gürtzgen (2006) on German data[28].

1.3 Data

Data for the analysis comes from two sources: the Hungarian Wage and Employment Survey (WES) provides information on the workers linked to various workplace characteristics, while data on collective and wage agreements are recorded by the Ministry of Social Affairs and Labor.

The WES is available from the National Employment Office for the years 1986, 1989, and 1992-2008. It includes all full time workers from tax-paying legal entities with double-sided balance sheets that employed at least 20 employees in 1986, extended to firms with at least 10 workers in 1995, and from 1999 on to micro-firms as well. Only firms from the enterprise sector are included. The linked database consists of various information on the worker (wage, gender, age, highest level of education defined by five educational categories, 4 digit occupational code) and also workplace characteristics (accounting information, such as the wage bill of the company, ownership, number of employees, 2-digit industry classification, region). Within firms, employees are sampled: on average, 6.5 percent of production workers and 10 percent of non-production workers got into the sample[29]. The database follows firms over time, but individuals do not have a consistent identifier through the years.[30]

[28] Detailed comparison of the Hungarian results to previously reported estimates will be given in the 5.3. Results section.
[29] Within firms, all production workers born on the 5th or the 15th of any month were questioned, and non-production workers got into the sample if born on the 5th, 15th or 25th of any month.
[30] A detailed analysis on the construction of the Hungarian WES is provided by Antal (2011).

The Ministry's records of agreement variables provide the best available data on collective contracting in Hungary, though it may suffer from union status misreporting. Data collection about wage agreements started in 1992. Since 1998, the Ministry of Labor extended the data collection to all collective contracts. Hence, compulsory registered collective agreements are available from 1998, though in many cases we have records for earlier years as well. The problem with both the wage and the collective agreement records is that though registration is compulsory, there is no sanctioning in case of unreported records.

The database on collective agreements includes information on the start and the end date of the collective contract. In many cases the duration of the collective contract is indefinite with no expiration date, which suggests that the collective contract has been in force since the start date. This is likely to be a good assumption, since the ministry is continuously monitoring the validity of these indefinite contracts and modifies the agreement record if necessary[31].

In the wage agreement records the same pieces of information are available as in the collective agreement records. However, there is an important difference between the administrative practice of collective and wage agreements: wage agreements are yearly negotiated. Thus, my wage agreement dummy is 1 only in the year of contracting unless the end date is explicitly specified in the contract[32].

[31] In spite of the careful monitoring it is possible that there are erroneous contract-years. However, there are several reasons to believe that "union reported when actually non-union" type misreporting is not frequent. First, never-union firms have no incentive to report, since reporting is an administrative burden. Second, ever-union firms, whose collective agreement has expired and not renewed are removed from the database due to the careful monitoring of the Ministry.
Due to the fact that non-reporting is not sanctioned, misreporting is more likely in the other direction: non-union status (i.e. no collective contract) is observed when the firm is actually a union (i.e. there is a collective contract). Since compulsory registration started only in 1998, non-reporting is likely to be more frequent in the years before 1998.

[32] Thus, in case of the wage agreement records non-reporting is likely to be more frequent than false reporting. Moreover, as data collection on wage agreements started in 1992, nonreported cases are probably not systematically larger before and after 1998.

After constructing the raw agreement variables from the Ministry data, I cleaned some obvious and likely erroneous cases to avoid spurious status switches within firms. First, I found 390 firm-years when wage agreement was reported, while collective agreement was not reported. Since by definition, wage agreements are also collective agreements, I corrected the collective agreement variable in those firm-years from zero to one. Second, I tried to detect spurious contract status switches. The most likely candidates are firms changing their status frequently as these cases may be indicative of negligent data reporting. Status switches should be less frequent in case of the collective agreement variable. I found nine firms having the following collective agreement records in five consecutive years: one, one, zero, one, one. I corrected the collective agreement variable in those nine cases from zero to one. Spurious status switches in case of the wage agreement variable are less obvious due to the practice of yearly negotiations. I considered the following cases as being indicative of non-reporting. If the wage agreement dummy takes one, zero, one values in three consecutive years and the collective agreement dummy is one in the middle year, then the wage agreement dummy is cleaned from zero to one in the middle year. In this way, I corrected 353 firm-years. These are the changes I made to the raw agreement variables, from here on the cleaned variables will be used.

The database was restricted in several way to ensure the consistency of the data and to construct an adequate comparison group. As the agreement data is only available for the years 1992 – 2006, I dropped the years before 1992 and after 2006. Then, I dropped those groups of firms where union coverage was very low. Table 1.1 depicts union coverage by the size of the firm and indicates that union coverage is very low in small firms. Thus, firms with less than 20 employees are dropped from the database. Dropping these firms also eliminates the sampling differences before and after 1995. As a next step, I examined the coverage of firms in the different industry categories. Regarding the collective agreement variable, coverage ranges from zero coverage to 77 percent through the different NACE2 categories. The coverage when using the wage agreement variable runs from zero to 42 percent. To get rid of categories with very low coverage, I decided to drop those 2-digit NACE categories where less than 5 percent of the employees are covered by a collective agreement[33]. Table 1.2 presents the number of firms and coverage in the union and non-union categories each year after the cleaning and the sample selection procedure. For example, in 2000, 14.6 percent of firms was covered by collective agreement, which accounts for 34 percent of employees. The final database consists of more than 1.5 million employee-year and 82,192 firm-year observations. The number of status switches within firms, which is the crucial factor of identification in the firm-FE models, is depicted by Table 1.3. The numbers are promising: the database provides 1,415 status switches in case of the collective agreement variable, and 2,944 switches of the wage agreement variable.

Some descriptive statistics of the two groups of firms (firms with and without collective agreement) are summarized by Table 1.4. Firms in the union group tend to be much larger and have slightly less advantageous worker composition than non-union firms. For example, the proportion of employees with university degree and high school is smaller in the union group, the union group tends to have a larger share of blue-collar workers, and a smaller share of employees aged below 30. However, the raw average wage is somewhat larger in the union group as confirmed by both wage variables. Thus, the first impression from the descriptive statistics is that the union group includes, on average, observably slightly “worse” employees, however, it may well be the case that union firms have higher unobservable attributes (e.g. better organizational structure, more effective management, more motivated workers, etc.). The regression analysis will try to answer this question.

[33] I dropped the following industry categories (NACE classification): 67, 71, 75, 80, 85, 91. This procedure reduced the firm-level sample by 3,452 observations.

1.4 Methodology

Following Farber (2001), the union – non-union wage gap will be defined as

$$\Delta_i = \frac{W_i^u - W_i^n}{W_i^n} \qquad (1)$$

where the subscript *u* refers to union status and the subscript *n* refers to non-union status. If the gap is sufficiently low, then it can be approximated by the difference in log wages. Unfortunately, for a given observational unit *i*, either status *u* or status *n* is observed, not both. There are several methods to compute the missing counterfactual.

If the observational units are randomly assigned to union and non-union status, then the wage gap can be computed as the difference in average wages between the two categories. However, this would rarely happen as Table 1.1 and the analysis in the Data section confirm. For example, in Hungary, firms with contract status are systematically larger and are concentrated in certain industries.

If we believe that sorting into union – non-union status is governed by observable characteristics, then the wage gap can be approximated by obtaining an estimate of the union dummy from the following individual-level equation (2):

$$\ln W_{ijt} = \alpha \cdot U_{jt} + \gamma \cdot \Gamma + \varepsilon_{ijt} \text{ with } \Gamma = \left(X_{ijt}, Z_{jt}\right) \text{ and } \varepsilon_{ijt} \sim N(0, \sigma_{\varepsilon}),$$

where *i* refers to the individual and *j* denotes the firm where the individual is employed. The causal effect of unions on wages is represented by α, the contract dummy is *U*, and the Γ matrix includes individual-level (summarized by X_{ijt}) and firm-level (summarized by Z_{jt}) controls. Early studies from the US and UK included mostly individual controls, such as the gender, age, education, occupation or tenure of the employee. As these studies were often based on household surveys, they had only limited information about the firm. With the increasing availability of linked employer-employee data, rich variety of firm-level controls can be added into the regressions. These latter studies indicate that controlling for firm-level observable variables reduces substantially the union wage gap. For example, Gürtzgen (2006) using German data and introducing controls step by step concludes that the largest portion of omitted variable bias is due to firm-level observables. Recent studies from the US based on enterprise level data also emphasize the role of firm-level controls. For example, DiNardo and Lee (2004) documented no wage impact of union coverage using a recent sample of US establishments that changed union status as a result of a union certification election. Their estimates sharply contrast previous results based on individual-level wages, which documented a union premium on the order of 15 percent in the US. Similarly, Lalonde, Marschke and Troske (1996), Freeman and Kleiner (1990) found very small or insignificant union wage effects analyzing the wage impact on the level of the firm.

If sorting into union status is governed by unobservable characteristics, then omitting these variables among the regressors will result in biased $\hat{\alpha}$. The reason is that the impact of unobserved variables being correlated with both union status and wages will be incorporated into the union variable. Assuming that the union wage impact is positive, positive correlation between the unobservables and the union dummy results in upward biased OLS estimates, while negative correlation causes the OLS estimates downward biased. It is widely believed in the literature that union status is not exogenous. Lewis (1986) argues that union workers are likely to have higher unobserved skills, as unionized employers will try to hire the most able workers to offset the effect of higher wages. The two-sided selection model (see e.g. Card 1996) goes one step further and takes into account the decisions of both the employer and employee. Accordingly, employers will choose the best employees from the pool, but workers with high observed skills will have incentive to enter union status only having low unobserved skills. Thus, workers with low observed skills are positively, while those with high observed skills will be negatively selected[34].

Selection may also occur along unobservable firm attributes. For example, DiNardo and Lee (2004) argue that unions are more likely to be organized in highly successful firms with good profit opportunities. As profit opportunities may depend on various unobservable factors, such as the organizational structure or the management of the firm, accounting for firm-level unobservables may decrease the union wage premium.

There are different ways to deal with the selection issue. Single-index selection models (e.g. Robinson 1989) are questioned by several researchers due to the instability of estimates. Moreover, they cannot be reconciled with the two-sided selection model. In the paper I apply another approach and use the longitudinal nature of the data to take into account firm-level unobservables. Units of observations are followed over time and their changes in union status are used for identification. Thus, after the OLS specification I estimate the following firm-FE model (3):

$$\ln W_{ijt} = \alpha \cdot U_{jt} + \gamma \cdot \Gamma + \varepsilon_{ijt} \text{ with } \Gamma = \left(X_{ijt}, Z_{jt}\right),\ \varepsilon_{ijt} = \nu_j + \eta_{ijt} \text{ and } \eta_{ijt} \sim N(0, \sigma_\eta),$$

where the error term ε is composed of a firm-fixed effect ν and a random noise component η. Though it is not possible to take into account selection along individual unobservables as the database does not follow individuals over time, one can introduce worker-group-firm fixed effects (WGFE) interacting the firm fixed effects with worker groups[35]. I classify workers into groups by gender, three educational and three age categories and also obtain estimates eliminating WGFE using specification (3).

[34] Card (1996) documents evidence of the two-sided selection using a 1987-88 panel set from the US Current Population Survey. On average, his longitudinal estimates (17 percent) are similar to the cross-sectional results (15-16 percent) implying that the two types of selection offset each other, but the estimates by worker skill indicate the two-sided selection pattern.

[35] Similar approach was used by Antal, Earle and Telegdy (2011) to analyze the impact of foreign acquisitions on wages.

The Hungarian WES provides opportunity to analyze the wage impact of contract status both on the level of the individual and on the level of the firm. The firm-level analogue of the previous individual specification is as follows (4):

$$\ln W_{jt} = \alpha \cdot U_{jt} + \gamma \cdot \Gamma + \varepsilon_{jt} \text{ with } \Gamma = \left(\overline{X}_{jt}, Z_{jt}\right),\ \varepsilon_{jt} = \nu_j + \eta_{jt} \text{ and } \eta_{jt} \sim N(0, \sigma_\eta),$$

where W_{jt} is the average wage at firm *j* at year *t* computed as the mean of employees' gross monthly wages or by dividing the accounting wage cost measure by the number of employees. $\overline{X}_{jt}$ controls for the same employee characteristics as used in the individual specifications, but in the form of proportions (proportion female, proportion of employees with different level of education, proportion of employees in the various age brackets, proportion of employees in the different occupational categories), and Z_{jt} includes the identical set of firm-level variables as in specifications (2) and (3).

There is a vivid discussion in the literature if the union wage impacts should be assessed at the level of individual or at the level of firm. According to Lewis (1986), union wage impact coming from aggregated wage equations exceeds those using individual earnings. The reasoning behind is that the number of explanatory variables is less in the aggregated equations, hence, union dummy may also capture the impact of omitted variables. However, this explanation should be considered with caution since linked employer-employee databases are available, thus, all individual-level variables can be included among the firm-level regressors in the form of proportions (e.g. proportion female or the proportion of employees with university degree). According to Pencavel (1991), the "right" level of aggregation is not necessarily the individual worker, since bargained wages usually do not differ by all sorts of worker characteristics, they are rather base salaries, perhaps adjusted by skill and experience categories. Recent studies from the US (DiNardo and Lee 2004, Freeman and Kleiner 1990, Lalonde, Marschke and Troske 1996) based on establishment data identify much smaller, mostly insignificant union wage impacts than previous studies using individual household survey data. However, so far, no study attempted to provide both firm- and individual-level estimates using the same dataset. Theoretically, an identical estimate of union wage impact should be identified from individual and firm-level databases using the same controls[36] and weighting the firm-level estimates by the number of workers observed at the firm (Card and de la Rica, 2006).

In the Hungarian case, the firm-level analysis of the union wage gap may be more appropriate due to several reasons. First, the contract dummy is defined on the level of the firm. As discussed by Fodor-Nacsa-Neumann (2008), wage agreements usually set only minimum requirements or define the extent of average wage growth in the firm, but do not include detailed specifications relating to the individual. Moreover, by defining firms as the units of observations, the problem of selection on individual unobservables is eliminated. Finally, the firm-level analysis allows using a variety of wage measures. One possibility is the mean of individual wages within the company. Besides, an accounting information, the total wage bill can be used, which may be more accurate than the mean of individual wages calculated from a survey of individuals. However, the firm-level analysis cannot be used to address distributional issues, such as the impact of collective contracts on different types of employees.

In the paper I assess the wage impact of contract status using several methods and specifications. Besides providing estimates both on the individual and firm level, I experiment with two types of contract dummies, and estimate the wage gap using separately the collective agreement or wage agreement dummies, and including both variables into the regression.

First, individual equations are estimated including controls step by step. As a start, the raw union wage gap is calculated having only time dummies in the regression beside

[36] For example, when female dummy is included in the individual equations, then the proportion female should be included in the firm-level analysis.

the contract variables. Next, equation (2) is estimated including additionally individual controls (X_{ijt}: gender, three educational, three age and five occupational categories):

$$\ln W_{ijt} = \alpha \cdot U_{jt} + \gamma \cdot \Gamma + \varepsilon_{ijt} \text{ with } \Gamma = (X_{ijt}) \text{ and } \varepsilon_{ijt} \sim N(0, \sigma_\varepsilon).$$

Then, equation (2) is estimated using both individual (X_{ijt}) and firm-level controls (Z_{jt}: size of the firm, ownership, 19 industry categories, 5 regions) :

$$\ln W_{ijt} = \alpha \cdot U_{jt} + \gamma \cdot \Gamma + \varepsilon_{ijt} \text{ with } \Gamma = (X_{ijt}, Z_{jt}) \text{ and } \varepsilon_{ijt} \sim N(0, \sigma_\varepsilon).$$

Finally, firm fixed effects and WGFE estimates are provided as specified in (3):

$$\ln W_{ijt} = \alpha \cdot U_{jt} + \gamma \cdot \Gamma + \varepsilon_{ijt} \text{ with } \Gamma = (X_{ijt}, Z_{jt}),\ \varepsilon_{ijt} = \nu_j + \eta_{ijt} \text{ and } \eta_{ijt} \sim N(0, \sigma_\eta).$$

The firm-level specifications follow the same logic as outlined above. Thus, first the raw union wage gap is estimated having only year controls. Then, worker composition controls are added (proportion female, proportion of employees with university degree, proportion of employees with high school, proportion aged over 50, proportion aged 30-50, and proportion of employees in five occupational categories). In the next step, the Z_{jt} control variables are included, and in the final FE specification firm fixed effects are eliminated:

$$\ln W_{jt} = \alpha \cdot U_{jt} + \gamma \cdot \Gamma + \varepsilon_{jt} \text{ with } \Gamma = (\overline{X}_{jt}, Z_{jt}),\ \varepsilon_{jt} = \nu_j + \eta_{jt} \text{ and } \eta_{jt} \sim N(0, \sigma_\eta).$$

In the firm-level specifications two types of wage measures (W_{jt}) can be used. One candidate is the mean of the individuals' wages observed at the firm. Another possibility is to use an accounting measure, the wage bill of the company, and construct average wage as wage bill divided by the number of employees. I will provide firm-level estimates using both variables.

1.5 Results

1.5.1 Individual-level results

The individual-level regression results are summarized by Table 1.5. First, results including either the collective agreement or the wage agreement dummy are discussed. The raw wage gap is 20-23 percent, which slightly decreases when including individual controls to a level of 17-19 percent. Firm-controls are responsible for a substantial drop of the union coefficient: the wage gap diminishes to 5.5 – 5.9 percent. Including firm fixed effects further decreases the gap to a level of 1.7 – 2.6 percent, which slightly drops when WGFE are also eliminated. In the final specification including WGFE, the raw wage gap of 23 percent decreases to 1.6 percent in case of the collective agreement variable, and the 20.7 percent raw wage gap drops to 1.3 percent when using the wage agreement variable. Comparing the results with either the collective or the wage agreement dummy, it is interesting to see that collective contract estimates are somewhat higher. A priori it is unclear if the collective or the wage agreement dummy captures best the power of unions. From one point of view, one would expect that the wage contract status is more appropriate as wage agreements constitute the subset of collective contracts, which explicitly include regulations on wages. Moreover, we would also expect that "union reported when non-union" type of false reporting is less frequent in case of the wage agreements. On the other hand, it is possible that the mere presence of an organized union, which is able to conclude a collective agreement, is enough to secure higher wages. The slightly higher collective contract estimates are somewhat puzzling, and suggest that the latter explanation may be relevant. To get more insight into the relative importance of collective and wage agreements, I estimated all the specifications including both agreement variables into the regression. Results are summarized by the bottom panel of Table 1.5, and show that wage agreements secure somewhat higher wages than collective contracts, though the additional return of wage agreements compared to collective contracts in the final WGFE specification is low. The wage gap for firms having only collective contracts is 1.2 percent, and firms having wage agreements offer, on average, 2.2 percent higher wages.

Besides the above regression including jointly the agreement variables, I experimented with some other specifications to provide more detailed analysis of the relative importance of the different agreement variables. These results are summarized by Table 1.6. First, I re-estimated the model, which included only the wage agreement variable excluding those observations, which had only collective contract without having wage agreement. In this way, the comparison group is probably better specified of having only non-covered firms, especially if collective contracts already secure somewhat higher wages[37]. The estimates mirror the results obtained in the specification including jointly the agreement variables: the wage agreement raw gap (compared to non-covered firms) of 26 percent drops to 2.2 percent in the WGFE specification. Next, I tried to identify the wage impact of collective agreements using those firms, which have only collective agreement without wage contract. The estimates are shown in the second panel of Table 1.6 and are similar to those obtained in the equation with both agreement variables: firms having only collective agreement (thus, no wage agreement) offer, on average, 1.2 percent higher wages according to the WGFE specification. The final experiment uses only those observations, which have some sort of collective agreement, and analyze the effect of wage agreements compared to collective agreements only on the subsample of contract firm-years. The results are summarized in the third panel of Table 1.6, and confirm the familiar

[37] The comparison of wage agreement and collective agreement estimates may be also distorted in the specifications including only one agreement dummy if other control variable estimates are sufficiently different in the two equations. However, it is probably not the main reason of the lower union estimates in the only-wage-agreement specification as the full set of regression results in the Appendix Tables 1.12 - 1.14.confirm. The estimates of the other control variables in the only-wage-agreement and in the only-collective-agreement cases are almost identical.

estimate of one additional percent wage advantage in firms with wage agreement compared to firms with only collective agreement (WGFE case).

In sum, individual-level results imply positive significant, though low wage gap estimates. According to the final WGFE results, firms with only collective agreements offer, on average, 1.2 – 1.3 percent higher wages than non-covered firms, while firms concluding also wage agreements provide 2.2 percent higher wages than non-covered firms. Therefore, not only firm-level wage contracts, but the presence of an organized union at the firm being able to conclude collective contract, is enough to secure slightly higher wages. The raw wage gap of 20-26 percent drops a bit when including individual controls, and reduces substantially after having firm controls among the regressors. The inclusion of firm fixed effects and WGFE diminishes further the results, which implies that though most of the selection into union status occurs along observable firm characteristics, unobservable firm-level variables also play a role, and "better" firms are non-randomly selected into the union status. The pattern and the magnitude of the results across the specifications are similar to Gürtzgen (2006) documenting that the 18-20 percent raw wage gap of firm-level contracts in Germany decreases by roughly 70 percent after including both individual and firm observables with a substantially larger drop due to firm variables. In her final fixed effects specification the wage gap due to firm-level agreements is minor: significant 2 percent, but only in Eastern Germany[38]. Card and de la Rica (2006) concludes similarly that in Spain the raw wage gap of 32-34 percent decreases by around 70 percent after controlling for observable individual and firm characteristics. Before turning to a deeper comparison of the Hungarian results to those obtained elsewhere, I present the firm-level results.

[38] In Western Germany only industry-level contracts were found to be significant, and suggested a 2 percent wage premium.

1.5.2 Firm-level results

Firm-level analysis provides opportunity to assess the wage impact of the agreements at a higher level of aggregation, and to make use of the two types of wage measures. Based on the results on the relative importance of the collective and wage agreement variable using individual-level data, I will provide estimates only in the following cases. First, the specifications including only the collective agreement dummy will be estimated. Then, I assess the impact of wage agreements compared to non-covered firms (to have a more adequate comparison group as explained in the previous section). The final specifications include both type of agreement variables. Table 1.7 summarizes the firm-level estimates. The main conclusion is the same as obtained in the individual specifications: most of the selection occurs along firm-level observables, and the wage gap in the final specification is small. The results using the mean of employees' wages as the dependent variable are close to the one obtained on individual data, though they are not identical[39]. The raw wage gap of 24 – 28 percent decreases slightly when including worker composition controls, and drops substantially by more than 70 percent after the inclusion of firm controls. In the final firm fixed effect specification the wage gap due to collective contracts is 2.6 percent, and the wage agreement premium relative to non-coverage is 3 percent. These results are somewhat higher than obtained on individual data, but qualitatively they yield the same conclusion: the wage advantage of collective contracts is tiny, at most 3 percent. Having both agreement variables in the equation, the magnitude of the estimates does not change, but they are statistically no longer significant.

[39] Using only firm-level controls defined by Z_{jt}, and applying proper weighting, firm-level and individual-level estimates are identical. However, including individual controls (X_{ijt} or $\overline{X}_{jt}$) results in minor discrepancy between the comparable firm-level and individual-level estimates.

The results using the wage bill per employee as the dependent variable suggest larger wage premium. The raw wage gap of 37 – 40 percent decreases to 7 – 8 percent in the final firm fixed effect specification. Another difference compared to previous results is that individual and firm-level observables explain only half of the raw wage gap, which decreases further by 70 percent when eliminating firm fixed effects. Contrary to the individual estimates, wage agreements do not yield significantly larger wage premium than collective contracts as implied by the specification with both agreement variables.

Theoretically, the two wage measures, based on the aggregation of individual data or on accounting information, are comparable. Individual wages in the WES include the monthly base wage, overtime pay, regular payments besides the base wage, and 1/12th of the previous year's bonuses. The accounting measure, the wage bill is defined as the total payments to workers (without the payroll tax and non-pecuniary benefits).[40] One difference between the two wage measures may come from the survey feature of the individual data: the wage bill is not sensitive to sampling issues, therefore, may be a more reliable measure of firm-level personal costs than the aggregation of individual wages[41]. The interpretation of firm-level "wage bill estimates" is perhaps more precisely formulated as how much more does an employer have to pay its workers when signing a collective contract. On the other hand, individual estimates may answer better the question of what would be the wage gain of an individual moving from an uncovered firm to a covered one (DiNardo and Lee 2004). Or, alternatively, in the Hungarian context, due to the similar content of both wage measures, one can interpret the "wage bill estimates" as an upper bound of the average contract premium.

[40] The definitions of the two wage measures (individual wages and total wage bill in the Hungarian WES) and more details on how they are constructed and on their comparability is found in Antal, Earle and Telegdy (2011), p 90, and in Antal (2011).

[41] A deeper comparison of the two wage measures would concern evaluating the different components of each measure, and experiment with various weighting techniques of the individual wages, and is left for future research.

In sum, the exercises of providing estimates both on individual and firm level data, suggest that the level of aggregation is not crucial when assessing the average wage gain of firm-level contracting: using analogous wage measures and properly weighting the observations, the individual wage gap estimate is 2.2 percent, and the firm-level estimate is 3 percent. On the other hand, using firm-level wage bill per employee as the dependent variable yields larger estimates in all specifications. As theoretically the discrepancy between the aggregated and the accounting wage measure may only stem from sampling and weighting issues of the individual data, I will consider the two values as lower and upper bounds of the wage premium.

1.5.3 Comparison of the results to previous estimates

Given the differences in the estimation method and the underlying institutional setting, the comparison of the Hungarian results to previously reported results from other countries is not straightforward. Studies from the continental Europe usually fail to detect substantial wage premium. For example, Gürtzgen (2006) documents maximum 2 percent wage premium of firm-level contracting relative to uncovered firms in Germany, and Hartog et al (2001) finds insignificant wage advantage associated with firm level contracts relative to industry-level contracting in the Netherlands. Both authors propose a possible interpretation of their results as being the consequence of the highly corporatist system, which prevents unions to behave as "aggressive local rent-seekers"[42]. Card and de la Rica (2006) finds a 5-10 percent wage premium of firm contracting relative to industry contracts in Spain with higher gains in case of more highly paid workers. According to the authors,

[42] Hartog et al (2002) describes the Dutch labor market as a system where different bargaining regimes coexist and are "embedded in a corporatist web". In this environment, though the prevailing level of bargaining is the intermediate one, unions do not operate as "aggressive local rent-seekers" (p 322). A similar logic may apply to Germany by Gürtzgen (2006) where centralized unions are likely to internalize negative externalities and suppress wage demands.

this is the result of the Spanish system of extended sectoral contracts, which flatten wages across skill groups, while firm-level wage agreements lead to a more flexible wage structure.[43, 44] Estimates from the Anglo-Saxon countries are usually higher. The most cited number from the US is that the mean union wage gap is 15 percent based on Lewis (1986)'s work of summarizing the findings of 165 studies for the period 1967–1979. Blanchflower and Bryson (2004) documents an average union wage premium of 17.6 percent in the period of 1973-2001. Hirsch (2003) concludes that the "Lewis consensus" is too low and estimates a union-nonunion wage gap in excess of 20 percent for 1973-2001. Longitudinal estimates following workers over time detect smaller estimates of around 10 percent (Lewis 1986, Hirsch 2003). On the other hand, firm-level analyses (DiNardo and Lee 2004, Freeman and Kleiner 1990, Lalonde, Marschke and Troske 1996) obtain minor or insignificant wage advantages associated with unionism. These authors interpret the contrast of their findings to previous literature as being the consequence of the important role of firm controls, which were scarcely available in previous household surveys, and that new unionization in recent years is probably associated with smaller wage gains compared to unions, which were formed earlier and managed to gain more support over several decades.

The Hungarian results of 2.2 – 3 percent wage advantages associated with firm-level contracting are most comparable to the German (Gürtzgen 2006) and the US

[43] Card and de la Rica (2006) propose a simple rent-based argument as a possible explanation of the firm-level contract premium. To choose among the competing explanations for the contract premium (efficiency wage models, unmeasured ability, rent-sharing), they examine if there are differences in the job tenure by the contract status of the firm, and find that average tenure is two years longer in workplaces with firm-specific contracts.

[44] Note, however, there are important differences between the estimation methodologies applied by the above papers. Gürtzgen (2006) uses an individual database and eliminates individual and firm fixed effects. Hartog et al (2001) provides a cross-sectional firm-level analysis for the year 1991. Card and de la Rica (2006) uses an individual-level cross-sectional dataset, and controls for unobserved worker ability by including coworker characteristics among the controls, and observed firm-level characteristics are flexibly controlled by augmenting the wage equation with a low-order polynomial function of the estimated probability of having a firm-level contract.

There are also institutional differences between the three countries. While there are three types of regimes in Germany: no coverage, industrial coverage and firm coverage, sectoral agreements are practically extended to cover all firms in the Netherlands and in Spain.

enterprise-level estimates. Not only the magnitudes of the estimates are very similar, but one feature of the institutional setting is analogous: both of these studies assess the wage impact of firm-level coverage vs. no coverage[45]. Additionally, the methodological approaches applied in the above papers are also similar: all of these studies take into account firm-level observable and unobservable variables[46]. However, the underlying reasons behind the small wage impacts are probably closer to the US case referring to union decline in recent years[47]. On the other hand, the US and Hungarian trade unions have historically different roots. Unionism in the US was traditionally a strong institution, and it started to decline in the 80's due to the use of striker replacement workers, the increased opposition of managers to unionization and due to the more frequent use of labor-saving technologies (DiNardo and Lee 2004). In contrast, Hungarian trade unions had to reorganize themselves after the regime change, find their new roles in the new environment and cope with their social inheritance. The outcome became a fragmented institutional system with dominantly firm-level collective bargaining. The weak bargaining power of the fragmented firm-level unions is mirrored by the tiny union coefficient estimates. Note that this is the outcome hypothesized by Calmfors and Driffill (1998) implying lower union-wages under decentralized industrial relations.

The present results are also in line with previous estimates on Hungarian data. The current cross-sectional estimate of a 6-8 percent wage premium (specification including only observable individual and observable firm controls) due to wage agreement is

[45] On the other hand, the Dutch and the Spanish studies analyze the impact of firm-level coverage relative to industrial coverage due to the universal extension of sectoral agreements.
[46] Gürtzgen (2006) uses the panel nature of the data to eliminate firm fixed effects. DiNardo and Lee (2004) applies a regression discontinuity design and compares wage outcomes in firms that barely won and barely lost union certification election. Lalonde, Marschke and Troske (1996) uses a panel of firms and applies difference-in-difference and fixed effect estimator. Freeman and Kleiner (1990) surveying 203 establishments that faced elections and 161 control firms, also applies a before / after research design.
[47] On the other hand, one possible explanation of the small wage impact of collective agreements in Germany is the highly corporatist industrial setting (Gürtzgen 2006).

comparable to the findings of Neumann (2001) and Iga et al (2009)[48]. However, the present analysis suggests that contract-firms may be systematically better along unobservable attributes, and the panel estimates imply somewhat smaller wage impact of 2.2 – 3 percent.

The use of firm-level wage bill, which was not exploited in any of the previous studies, suggests that the firm-level costs associated with collective contracting may be even higher, and are comparable in magnitude to US household survey estimates. After controlling for individual and firm-level observables, the wage gap is 18-20 percent, which is quantitatively close to the cross-sectional estimates by Hirsch (2003). Though the final wage gap of 7-8 percent is somewhat below the 10 percent reference value of US longitudinal household survey estimates, it is surprisingly high given the fragmented institutional structure of industrial relations in Hungary.

1.5.4 Heterogeneity of results and robustness checks

After assessing on average the impact of firm-level agreements on firms' wage costs, I analyze in this section if the impact differs by period, by the size of the firm, and if the wage gap of the average worker varies by occupation. The first two questions are analyzed on firm-level data, and the occupational heterogeneities are studied on individual data. To simplify the interpretation, I provide estimates using only the wage agreement dummy[49].

As discussed in Section 1.2, the large increase of minimum wages, which started in 2001, implied in many cases a wage increase being larger than unions hoped for. Thus,

[48] Note however, the comparison of the results is not straightforward. Neumann (2001) uses the 1998 cross section of the WES and the Ministry's collective agreement records, but Iga et al (2009) uses the European Structure of Earnings Survey from 2002, which includes agreement records from other source.
[49] The comparison group is composed of non-covered firms, thus, firms having only collective agreement are excluded from the analysis. The results are robust to using alternatively the collective agreement dummy.

after 2000, wage agreements lost somewhat their importance, which is also reflected in their shrinking number in the most recent years. Therefore, it is interesting to see if the wage gap decreases after 2001. To analyze the question, I defined two periods: the first one covering the years 1992-2000, and the second one including the years 2001-2006, and interacted the wage agreement dummy with the period dummies. Results are shown by Table 1.8. The left columns summarize the estimates using the mean of individual wages as the dependent variable, while the right columns use the average wage bill. Results are provided in two specifications. The first specification includes only observable individual and observable firm characteristics besides the interacted agreement variables, while the second specification includes additionally firm fixed effects. The results suggest that the wage gap is indeed somewhat smaller in the later period. In the firm-FE specification the contract coefficient drops from significant 4 percent to insignificant by the second period using the individual wages, and it drops from 8.6 to 7.6 percent in case of the average wage bill.

The next experiment analyzes if the wage gap differs by the size of the firm. As confirmed by Table 1.1, agreement coverage is much larger in bigger firms. I define two size categories, firms with less (more) than 300 employees, and interacted the contract status dummy with the size category dummies. Results are presented by Table 1.9, and suggest that the wage gap is larger in bigger firms. In the firm-FE specification the wage premium is 3.2 percent in large firms and insignificant in smaller firms using the mean individual wages, while the similar estimates are 9.1 and 2.4 percent, respectively, in case of the average wage bill.

The final exercise examines if the wage gap differs by occupational group. Studies from the US based on household surveys indicate that union contracts lead to higher wages among the low skilled, and flatten wages across skill groups[50]. On the other hand, Card and de la Rica (2006) documents higher contract premium of more highly skilled workers in Spain where sectoral contracts are universally extended. In Hungary, where wage agreements usually set only minimum wages and minimum wage increases, and employers are given a considerable freedom to set higher individual wages than specified in the contract, one would expect that wage agreement requirements are more important for the low-earner employees. To carry out the exercise, I divided workers into two broad occupational groups: blue-collar and white-collar workers, and run separate regressions using the sample of blue-collar and white-collar workers. Table 1.10 summarizes the results for the specifications including only observable controls, eliminating firm-FE and WGFE. The estimates, in line with expectations, imply that basically all the wage advantages apply to blue-collar workers: none of the results on the white-collar sample are significant, while those obtained on the blue-collar sample are comparable to the previous estimates.

Measurement error of the union dummy received lots of attention in the literature (see for example Card 1996 or Hirsch 2003). Though it may be a relevant problem in studies based on household survey, it is much less so in an analysis using official agreement reports from firms. However, as specified in the Data section, the agreement data used in the paper may suffer from misreporting, especially in case of the collective contract dummy. To get some idea about the extent of bias caused by misreporting, I repeated the firm-level regressions without cleaning the contract variables (using the collective and wage agreement dummies in separate equations). As Table 1.11 shows, results are basically identical. Note, however, that the comparison is rather limited as the

[50] See for example, Card (1996). On the other hand, Hirsch and Schumacher (1998) obtain identical longitudinal wage gap estimates across educational groups.

cleaning procedure affected 360 collective-contract observations (out of the 10,111 cases) and 333 wage agreement observations (out of the 4,470 cases).

1.6 Conclusion

The conventional wisdom about unions in Hungary is that they are the heritage of centralized communist unions with small or no influence on wages. This paper aims to examine this statement and quantify the wage impact of unions using the best available database.

The results show that, on average, firm-level contracting is associated with 1.2 – 8.2 percent higher wages depending on specification. Using individuals' wages as the outcome measure, the average wage gap is 2.2 – 3 percent, and changes only slightly if estimation is carried out on the individual or on the firm level. Nevertheless, using the firm-level wage bill as the dependent variable, the final wage gap is larger, on the order of 6-8 percent.

The estimation results of the various specifications including more and more control variables are in line with the conclusions from previous studies (e.g. Card and de la Rica 2006, Gürtzgen 2006): a large portion of the selection into contract status occurs along firm-level observables. Additionally, Hungarian contract firms are also "better" along firm-level unobservable variables.

An interesting application of the Hungarian data is to experiment with the collective agreement and the wage agreement variables. The analysis confirms that, though wage agreements assure slightly higher wages than do only collective agreements, the mere presence of an organized union at the firm, which is able to conclude collective contract, is enough to secure higher wages.

The heterogeneity analysis in Section 1.5.4. suggests that firm-level contracts tend to raise the wages only of the blue-collar workers. This is in line with expectations knowing the features of Hungarian wage agreements. They usually assure small wage requirements, define mostly minimum wages, and leave considerable room for managers to decide on individual wages.

The heterogeneity analysis also suggests that the wage gap tends to be larger in larger firms employing at least 300 employees. Over time, on would expect that the wage gap becomes smaller as, starting from 2001, national minimum wages implied higher wage increases than unions hoped for. The estimates imply somewhat smaller premium for the period after 2000. However, with the introduction of the three-tier minimum wage system in 2006, current estimates might be even smaller.

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1.8 Tables

Table 1.1: Union coverage in the different employment-size categories in 2000

	collective agreement		wage agreement	
# employees	**firms covered (%)**	**employees covered (%)**	**firms covered (%)**	**employees covered (%)**
<20	2.2	3.0	1.0	1.0
20-50	5.0	4.0	2.0	1.6
50-100	13.6	15.4	6.1	5.7
100-300	36.0	39.9	19.0	21.1
300-500	63.2	67.6	42.2	49.5
>500	79.3	85.7	49.1	51.5

Table 1.2: Coverage of the agreement variables (after the cleaning procedure and sample selection)

	collective agreement			wage agreement		
	# agreements	firms covered (%)	employees covered (%)	# agreements	firms covered (%)	employees covered (%)
1992	18	0.4	0.6	6	0.1	0.2
1993	113	2.1	4.2	67	1.3	1.9
1994	300	5.4	16.3	136	2.5	5.8
1995	386	6.5	18.9	104	1.7	3.5
1996	501	8.7	20.1	145	2.5	4.9
1997	671	11.8	25.6	206	3.6	6.6
1998	962	17.0	35.3	475	8.4	19.3
1999	973	16.1	35.5	461	7.6	23.8
2000	999	14.6	34.0	515	7.5	19.7
2001	950	13.6	28.9	439	6.3	13.6
2002	886	18.3	39.0	461	9.5	19.4
2003	860	18.4	41.7	452	9.7	23.3
2004	877	16.8	36.2	487	9.3	25.3
2005	850	16.2	33.3	347	6.6	14.6
2006	765	15.6	32.3	169	3.4	9.8
Total (1992-2006)	10,111	12.1	26.8	4,470	5.3	12.8

Table 1.3: Number of status switches in the final firm-level database (after cleaning and sample selection)

	contract status switches			
	collective agreement		wage agreement	
	0 - 1 status switches	1 - 0 status switches	0 - 1 status switches	1 - 0 status switches
1992/1993	64	0	49	3
1993/1994	112	16	94	58
1994/1995	74	19	64	108
1995/1996	116	10	99	67
1996/1997	161	12	129	84
1997/1998	272	12	336	88
1998/1999	71	26	159	150
1999/2000	69	21	155	91
2000/2001	28	29	66	125
2001/2002	33	20	103	67
2002/2003	36	22	97	90
2003/2004	44	27	102	82
2004/2005	39	25	73	187
2005/2006	18	39	33	185
Total	1,137	278	1,559	1,385

Table 1.4: Descriptive statistics of union and non-union firms in 2000
Mean and standard deviation of selected variables. Standard deviation in Italic.

	union status defined by			
	collective agreement		wage agreement	
	union	non-union	union	non-union
# employees	463 *2,128*	56 *107*	525 *1,973*	66 *409*
proportion employees with degree	0.122 *0.209*	0.152 *0.305*	0.142 *0.246*	0.150 *0.302*
proportion employees with high school	0.316 *0.251*	0.437 *0.421*	0.319 *0.267*	0.433 *0.417*
proportion employees with elementary education	0.562 *0.298*	0.411 *0.426*	0.539 *0.308*	0.417 *0.424*
proportion white-collar	0.386 *0.304*	0.546 *0.448*	0.406 *0.314*	0.541 *0.445*
proportion blue-collar	0.614 *0.304*	0.454 *0.448*	0.594 *0.314*	0.459 *0.445*
ratio aged over 50	0.281 *0.249*	0.268 *0.370*	0.289 *0.257*	0.269 *0.367*
ratio aged 30-50	0.547 *0.249*	0.480 *0.399*	0.539 *0.252*	0.482 *0.396*
ratio aged below 30	0.172 *0.181*	0.252 *0.351*	0.172 *0.176*	0.249 *0.348*
proportion female	0.425 *0.321*	0.410 *0.418*	0.431 *0.319*	0.410 *0.415*
average wage bill (log, million HUF)	6.931 *0.428*	6.508 *0.624*	6.971 *0.422*	6.520 *0.623*
mean of individual wages (log, thousand HUF)	11.274 *0.444*	11.045 *0.654*	11.314 *0.407*	11.050 *0.650*
Obs	999	5,843	514	6,327

Table 1.5: Results of the individual level earning regressions

		raw gap	individual controls	firm controls	firm-FE	WGFE
including *only one* contract variable	collective agreement	0.229 *0.0272****	0.186 *0.0198****	0.0546 *0.0136****	0.0255 *0.00995***	0.0162 *0.00475****
	wage agreement	0.207 *0.0225****	0.173 *0.0200****	0.0588 *0.0125****	0.0166 *0.00448****	0.0130 *0.00228****
including *both* contract variables	collective agreement	0.205 *0.0301****	0.163 *0.0206****	0.0424 *0.0166***	0.0213 *0.0109**	0.0123 *0.00507***
	wage agreement	0.0665 *0.0224****	0.0621 *0.0174****	0.0372 *0.0173***	0.0104 *0.00512***	0.00972 *0.00242****
Obs		1,517,744	1,517,744	1,493,331	1,493,331	1,493,331

The table reports coefficients for the agreement variables. Standard errors in Italic, stars indicate significance levels: *p<0.1, **p<0.05, ***p<0.01. Standard errors are robust to firm-level clustering. The dependent variable is the gross monthly earning of the individual. Raw wage gap is estimated including time dummies. Individual controls include gender, education (three categories, age (three categories) and occupation (seven categories). Firm controls include ownership, size, 19 industry categories and 7 region dummies. Detailed results including all the coefficient estimates are in Appendix Tables 1.12. – 1.14.

Table 1.6: Individual level earning regressions, some alternative specifications with the collective and wage agreement dummies

		raw gap	individual controls	firm controls	firm-FE	WGFE
excluding firms with only collective agreement	wage agreement	0.261 *0.0124****	0.219 *0.00875****	0.0597 *0.00635****	0.0334 *0.00440****	0.0218 *0.00468****
	Obs	1,231,914	1,231,914	1,208,789	1,208,789	1,208,789
excluding observations with wage agreement	collective agreement	0.208 *0.0136****	0.167 *0.00919****	0.0334 *0.00724****	0.0229 *0.00530****	0.0127 *0.00573***
	Obs	1,328,190	1,328,190	1,304,657	1,304,657	1,304,657
excluding observations without collective agreement	wage agreement	0.0538 *0.0110****	0.0438 *0.00777****	0.0413 *0.00657****	0.00901 *0.00239****	0.00938 *0.00239****
	Obs	463,793	463,793	461,910	461,910	461,910

The table reports coefficients for the agreement variables. Standard errors in Italic, stars indicate significance levels: *p<0.1, **p<0.05, ***p<0.01. Standard errors are robust to firm-level clustering. The dependent variable is the gross monthly earning of the individual. Raw wage gap is estimated including time dummies. Individual controls include gender, education (three categories, age (three categories) and occupation (seven categories). Firm controls include ownership, size, 19 industry categories and 7 region dummies.

Table 1.7: Firm-level wage equation estimates

		dependent var	raw gap	individual controls	firm controls	firm-FE
including *only one* contract variable	collective agreement	mean of employees' wages	0.244 *0.0285****	0.235 *0.0198****	0.0639 *0.0171****	0.0262 *0.0112***
		wage bill per employee	0.368 *0.0399****	0.350 *0.0315****	0.183 *0.0225****	0.0728 *0.00903****
	Obs		82,192	82,192	81,497	81,497
	wage agreement	mean of employees' wages	0.282 *0.0276****	0.277 *0.0197****	0.0719 *0.0178****	0.0299 *0.0115****
		wage bill per employee	0.407 *0.0342****	0.394 *0.0257****	0.194 *0.0257****	0.0812 *0.00975****
	Obs		76,576	76,576	75,882	75,882
including *both* contract variables	mean of employees' wages	collective agreement	0.211 *0.0345****	0.200 *0.0233****	0.0390 *0.0229**	0.0204 *0.0139*
		wage agreement	0.0700 *0.0299***	0.0752 *0.0201****	0.0549 *0.0222***	0.0105 *0.00840*
	wage bill per employee	collective agreement	0.337 *0.0514****	0.315 *0.0408****	0.157 *0.0291****	0.0682 *0.0109****
		wage agreement	0.0652 *0.0418*	0.0734 *0.0316***	0.0571 *0.0266***	0.00829 *0.00855*
	Obs		82,192	82,192	81,497	81,497

The table reports coefficients for the agreement variables. Standard errors in Italic, stars indicate significance levels: *p<0.1, **p<0.05, ***p<0.01. Standard errors are robust to firm-level clustering. Raw wage gap is estimated including time dummies. Individual controls include within-firm proportion of female, share of employees within various educational (three categories), age (three categories) and occupational groups (7 categories). Firm controls include ownership, size, 19 industry categories and 7 region dummies. Detailed results including all the coefficient estimates are in Appendix Tables 1.15. – 1.17.

Table 1.8: Firm-level wage equation estimates by period

Period 1: 1992-2000
Period 2: 2001-2006

	dependent variable			
	mean of individual wages		average wage bill	
	specification			
	individual and firm observables	firm-FE	individual and firm observables	firm-FE
wage agr * period 1	0.0811	0.0418	0.199	0.0864
	*0.0244****	*0.0110****	*0.0312****	*0.00970****
wage agr * period 2	0.0631	0.0149	0.190	0.0746
	*0.0178****	*0.0148*	*0.0251****	*0.0136****
Obs	75,882	75,882	75,906	75,906

The table reports coefficients for the interacted agreement variables. Standard errors in Italic, stars indicate significance levels: *p<0.1, **p<0.05, ***p<0.01. Standard errors are robust to firm-level clustering. Time dummies included in all specifications. Individual controls include within-firm proportion of female, share of employees within various educational (three categories), age (three categories) and occupational groups (7 categories). Firm controls include ownership, size, 19 industry categories and 7 region dummies. Detailed results including all the coefficient estimates are in Appendix Table 1.18.

Table 1.9: Firm-level wage equation estimates by the size of the firm

Size 1: emp<300
Size 2: emp>=300

	dependent variable			
	mean of individual wages		average wage bill	
	specification			
	individual and firm observables	firm-FE	individual and firm observables	firm-FE
wage agr * size 1	0.152	0.0189	0.289	0.0235
	*0.0172****	*0.0118*	*0.0206****	*0.0111***
wage agr * size 2	0.0526	0.0318	0.171	0.0912
	*0.0211***	*0.0131***	*0.0311****	*0.0107****
Obs	75,882	75,882	75,906	75,906

The table reports coefficients for the interacted agreement variables. Standard errors in Italic, stars indicate significance levels: *p<0.1, **p<0.05, ***p<0.01. Standard errors are robust to firm-level clustering. Time dummies included in all specifications. Individual controls include within-firm proportion of female, share of employees within various educational (three categories), age (three categories) and occupational groups (7 categories). Firm controls include ownership, size, 19 industry categories and 7 region dummies. Detailed results including all the coefficient estimates are in Appendix Table 1.19.

Table 1.10: Individual level earning regression estimates on separate samples by occupational category (blue-collar vs. white-collar)

	Sample	specification		
		individual and firm observables	**firm-FE**	**WGFE**
wage agreement	**blue-collar**	0.0804 *0.00775****	0.0381 *0.00439****	0.0278 *0.00417****
	Obs	727,942	727,942	727,942
	white-collar	0.00858 *0.0108*	0.0112 *0.0105*	-0.00413 *0.0116*
	Obs	480,847	480,847	480,847

The table reports coefficients for the wage agreement variable. Standard errors in Italic, stars indicate significance levels: *p<0.1, **p<0.05, ***p<0.01. Standard errors are robust to firm-level clustering. The dependent variable is the gross monthly earning of the individual. Time dummies are included in all specifications. Individual controls include gender, education (three categories, age (three categories). Firm controls include ownership, size, 19 industry categories and 7 region dummies. The following occupational categories are defined as blue-collar: service, skilled manual, unskilled. White-collar occupational categories include managers, professionals, associate professionals, skilled non-manual. Detailed results including all the coefficient estimates are in Appendix Table 1.20.

Table 1.11: Firm level wage equation estimates using the original (without cleaning) and cleaned agreement variables

		dependent var	raw gap	individual controls	firm controls	firm-FE
collective agreement	without cleaning	mean of employees' wages	0.247 *0.0293****	0.236 *0.0202****	0.0659 *0.0173****	0.0259 *0.0117***
		wage bill per employee	0.370 *0.0411****	0.350 *0.0322****	0.182 *0.0228****	0.0747 *0.00960****
	after cleaning	mean of employees' wages	0.244 *0.0285****	0.235 *0.0198****	0.0639 *0.0171****	0.0262 *0.0112***
		wage bill per employee	0.368 *0.0399****	0.350 *0.0315****	0.183 *0.0225****	0.0728 *0.00903****
	Obs		82,192	82,192	81,497	81,497
wage agreement	without cleaning	mean of employees' wages	0.282 *0.0275****	0.276 *0.0200****	0.0713 *0.0175****	0.0290 *0.0115***
		wage bill per employee	0.407 *0.0341****	0.393 *0.0258****	0.193 *0.0254****	0.0809 *0.00981****
	after cleaning	mean of employees' wages	0.282 *0.0276****	0.277 *0.0197****	0.0719 *0.0178****	0.0299 *0.0115****
		wage bill per employee	0.407 *0.0342****	0.394 *0.0257****	0.194 *0.0257****	0.0812 *0.00975****
	Obs		76,576	76,576	75,882	75,882

The table reports coefficients for the agreement variables. Standard errors in Italic, stars indicate significance levels: *p<0.1, **p<0.05, ***p<0.01. Standard errors are robust to firm-level clustering. Raw wage gap is estimated including time dummies. Individual controls include within-firm proportion of female, share of employees within various educational (three categories), age (three categories) and occupational groups (7 categories). Firm controls include ownership, size, 19 industry categories and 7 region dummies.

1.9 Appendix

Table 1.12: Individual-level estimates (corresponding to Table 1.5)

	Raw wage gap	**individual controls**	**firm controls**	**firm FE**	**WGFE**
wage agreement	0.207	0.173	0.0588	0.0166	0.0130
	*0.0225****	*0.0200****	*0.0125****	*0.00448****	*0.00228****
female		-0.183	-0.173	-0.154	
		*0.00658****	*0.00640****	*0.00409****	
degree		0.642	0.574	0.424	
		*0.0156****	*0.0117****	*0.00939****	
high school		0.203	0.154	0.0956	
		*0.0109****	*0.00475****	*0.00396****	
aged 30-50		0.121	0.124	0.133	
		*0.00682****	*0.00571****	*0.00563****	
aged over 50		0.152	0.161	0.180	
		*0.0115****	*0.0105****	*0.00997****	
manager		0.130	0.723	0.310	0.297
		*0.0167****	*0.0204****	*0.0195****	*0.0112****
professional			0.531		
			*0.0151****		
associate professional		-0.137	0.371	-0.108	-0.0956
		*0.0201****	*0.0217****	*0.0157****	*0.0105****
skilled non-manual		-0.289	0.275	-0.218	-0.210
		*0.0177****	*0.0104****	*0.0126****	*0.00999****
service		-0.468	0.0779	-0.323	-0.309
		*0.0245****	*0.0225****	*0.0190****	*0.0126****
skilled manual		-0.312	0.259	-0.242	-0.228
		*0.0180****	*0.00947****	*0.0133****	*0.0147****
unskilled		-0.593		-0.463	-0.442
		*0.0165****		*0.0107****	*0.0137****
ownership (private=1)			0.0996	0.0540	0.0515
			*0.0203****	*0.0144****	*0.00654****
logL			0.0505	0.00855	0.0135
			*0.00670****	*0.00723*	*0.00347****
year summies	yes	yes	yes	yes	yes
industry dummies	no	no	yes	yes	yes
region dummies	no	no	yes	yes	yes
Obs	1,517,744	1,517,744	1,493,331	1,493,331	1,493,331
R-squared	0.569	0.731	0.769	0.863	0.897

Standard errors in Italic, stars indicate significance levels: *p<0.1, **p<0.05, ***p<0.01. Standard errors are robust to firm-level clustering.

Table 1.13: Individual-level estimates (corresponding to Table 1.5)

	Raw wage gap	**individual controls**	**firm controls**	**firm FE**	**WGFE**
collective agreement	0.229	0.186	0.0546	0.0255	0.0162
	*0.0272****	*0.0198****	*0.0136****	*0.00995***	*0.00475****
female		-0.183	-0.174	-0.154	
		*0.00648****	*0.00658****	*0.00409****	
degree		0.642	0.574	0.424	
		*0.0154****	*0.0117****	*0.00940****	
high school		0.198	0.153	0.0955	
		*0.0104****	*0.00466****	*0.00398****	
aged 30-50		0.114	0.123	0.133	
		*0.00692****	*0.00591****	*0.00562****	
aged over 50		0.144	0.159	0.180	
		*0.0119****	*0.0106****	*0.00996****	
manager		0.135	0.721	0.310	0.297
		*0.0167****	*0.0203****	*0.0196****	*0.0112****
professional			0.529		
			*0.0150****		
associate professional		-0.142	0.368	-0.108	-0.0955
		*0.0219****	*0.0219****	*0.0157****	*0.0105****
skilled non-manual		-0.282	0.273	-0.218	-0.210
		*0.0171****	*0.0104****	*0.0126****	*0.00999****
service		-0.474	0.0752	-0.322	-0.309
		*0.0247****	*0.0223****	*0.0189****	*0.0126****
skilled manual		-0.305	0.258	-0.242	-0.228
		*0.0174****	*0.00934****	*0.0132****	*0.0147****
unskilled		-0.580		-0.463	-0.442
		*0.0155****		*0.0107****	*0.0137****
ownership (private=1)			0.0998	0.0509	0.0497
			*0.0201****	*0.0146****	*0.00665****
logL			0.0475	0.00906	0.0138
			*0.00683****	*0.00721*	*0.00346****
year summies	yes	yes	yes	yes	yes
industry dummies	no	no	yes	yes	yes
region dummies	no	no	yes	yes	yes
Obs	1,517,744	1,517,744	1,493,331	1,493,331	1,493,331
R-squared	0.569	0.731	0.769	0.863	0.897

Standard errors in Italic, stars indicate significance levels: *p<0.1, **p<0.05, ***p<0.01. Standard errors are robust to firm-level clustering.

Table 1.14: Individual-level estimates (corresponding to Table 1.5)

	Raw wage gap	individual controls	firm controls	firm FE	WGFE
collective agreement	0.205	0.163	0.0424	0.0213	0.0123
	*0.0301****	*0.0206****	*0.0166***	*0.0109**	*0.00507***
wage agreement	0.0665	0.0621	0.0372	0.0104	0.00972
	*0.0224****	*0.0174****	*0.0173***	*0.00512***	*0.00242****
female		-0.182	-0.174	-0.154	
		*0.00633****	*0.00640****	*0.00409****	
degree		0.642	0.574	0.424	
		*0.0151****	*0.0116****	*0.00941****	
high school		0.198	0.153	0.0955	
		*0.0103****	*0.00470****	*0.00397****	
aged 30-50		0.113	0.123	0.133	
		*0.00683****	*0.00581****	*0.00562****	
aged over 50		0.143	0.159	0.180	
		*0.0119****	*0.0105****	*0.00996****	
manager		0.135	0.721	0.310	0.297
		*0.0167****	*0.0204****	*0.0196****	*0.0112****
professional			0.529		
			*0.0150****		
associate professional		-0.141	0.369	-0.108	-0.0955
		*0.0217****	*0.0214****	*0.0157****	*0.0105****
skilled non-manual		-0.283	0.273	-0.218	-0.210
		*0.0171****	*0.0104****	*0.0126****	*0.00998****
service		-0.474	0.0757	-0.322	-0.309
		*0.0247****	*0.0221****	*0.0190****	*0.0126****
skilled manual		-0.305	0.258	-0.242	-0.228
		*0.0175****	*0.00931****	*0.0133****	*0.0146****
unskilled		-0.581		-0.463	-0.442
		*0.0155****		*0.0107****	*0.0137****
ownership (private=1)			0.101	0.0513	0.0501
			*0.0202****	*0.0148****	*0.00670****
logL			0.0472	0.00901	0.0138
			*0.00682****	*0.00722*	*0.00346****
year summies	yes	yes	yes	yes	yes
industry dummies	no	no	yes	yes	yes
region dummies	no	no	yes	yes	yes
Obs	1,517,744	1,517,744	1,493,331	1,493,331	1,493,331
R-squared	0.577	0.736	0.769	0.863	0.897

Standard errors in Italic, stars indicate significance levels: *p<0.1, **p<0.05, ***p<0.01. Standard errors are robust to firm-level clustering.

Table 1.15: Firm-level estimates (corresponding to Table 1.7)

	mean of individual wages				average wage bill			
	raw wage gap	individual controls	firm controls	firm FE	raw wage gap	individual controls	firm controls	firm FE
collective agreement	0.244	0.235	0.0639	0.0262	0.368	0.350	0.183	0.0728
	*0.0285****	*0.0198****	*0.0171****	*0.0112***	*0.0399****	*0.0315****	*0.0225****	*0.00903****
share female		-0.156	-0.110	-0.0976		-0.195	-0.145	-0.0244
		*0.0400****	*0.0415****	*0.0284****		*0.0361****	*0.0386****	*0.0228*
share with degree		0.803	0.663	0.426		0.828	0.627	0.0794
		*0.0754****	*0.0732****	*0.0478****		*0.0759****	*0.0631****	*0.0327***
share with high school		0.400	0.287	0.0951		0.409	0.270	0.0114
		*0.0427****	*0.0345****	*0.0237****		*0.0480****	*0.0357****	*0.0148*
share aged 30-50		-0.0602	-0.00146	0.104		-0.182	-0.120	-0.0410
		0.0630	*0.0465*	*0.0441***		*0.0486****	*0.0395****	*0.0180***
share aged over 50		0.00146	0.0743	0.129		-0.227	-0.152	-0.0913
		0.0603	*0.0472*	*0.0514***		*0.0619****	*0.0549****	*0.0223****
share managers		-0.326	-0.162	0.135		-0.877	-0.706	-0.176
		*0.142***	*0.139*	*0.0583***		*0.157****	*0.143****	*0.0545****
s. associate profess.		-0.319	-0.343	-0.125		-0.423	-0.515	-0.123
		*0.151***	*0.150***	*0.0717**		*0.176***	*0.161****	*0.0575***
s. skilled non-manual		-0.539	-0.450	-0.247		-0.532	-0.465	-0.136
		*0.159****	*0.160****	*0.0700****		*0.179****	*0.165****	*0.0663***
share service		-0.669	-0.728	-0.505		-0.641	-0.684	-0.166
		*0.148****	*0.148****	*0.115****		*0.161****	*0.150****	*0.0638****
share skilled manual		-0.332	-0.310	-0.342		-0.357	-0.302	-0.148
		*0.142***	*0.140***	*0.0656****		*0.159***	*0.145***	*0.0658***
share unskilled		-0.704	-0.655	-0.550		-0.664	-0.576	-0.162
		*0.145****	*0.146****	*0.0622****		*0.162****	*0.153****	*0.0630***
ownership (private=1)			0.0699	0.0361			0.105	0.0552
			*0.0203****	*0.0146***			*0.0303****	*0.0204****
logL			0.0600	0.00740			0.0495	-0.0793
			*0.00686****	*0.00960*			*0.00843****	*0.0108****
year dummies	yes	yes	yes	yes	yes	yes	yes	yes
industry dummies	no	no	yes	yes	no	no	yes	yes
region dummies	no	no	yes	yes	no	no	yes	yes
Obs	82,192	82,192	81,497	81,497	82,213	82,213	81,519	81,519
R-squared	0.614	0.716	0.759	0.942	0.581	0.662	0.730	0.969

Standard errors in Italic, stars indicate significance levels: *p<0.1, **p<0.05, ***p<0.01. Standard errors are robust to firm-level clustering. Reference categories are as follows: share male, share primary school, share aged below 30, share professionals.

Table 1.16: Firm-level estimates (corresponding to Table 1.7)

	mean of individual wages				average wage bill			
	raw wage gap	individual controls	firm controls	firm FE	raw wage gap	individual controls	firm controls	firm FE
wage agreement	0.282	0.277	0.0719	0.0299	0.407	0.394	0.194	0.0812
	*0.0276****	*0.0197****	*0.0178****	*0.0115****	*0.0342****	*0.0257****	*0.0257****	*0.00975****
share female		-0.142	-0.0973	-0.109		-0.179	-0.120	-0.0155
		*0.0402****	*0.0367****	*0.0138****		*0.0361****	*0.0358****	*0.0232*
share with degree		0.755	0.618	0.375		0.774	0.587	0.0444
		*0.0759****	*0.0729****	*0.0436****		*0.0729****	*0.0610****	*0.0338*
share with high school		0.380	0.279	0.104		0.376	0.248	0.00330
		*0.0422****	*0.0319****	*0.0196****		*0.0477****	*0.0347****	*0.0151*
share aged 30-50		-0.0835	-0.0173	0.0587		-0.199	-0.132	-0.0312
		0.0612	*0.0430*	*0.0161****		*0.0478****	*0.0386****	*0.0183**
share aged over 50		-0.0137	0.0621	0.0815		-0.240	-0.163	-0.0764
		0.0599	*0.0452*	*0.0214****		*0.0619****	*0.0554****	*0.0228****
share managers		-0.295	-0.142	0.182		-0.819	-0.664	-0.124
		*0.139***	*0.137*	*0.0493****		*0.150****	*0.137****	*0.0362****
s. associate profess.		-0.293	-0.319	-0.118		-0.347	-0.444	-0.0702
		*0.148***	*0.146***	*0.0494***		*0.167***	*0.154****	*0.0411**
s. skilled non-manual		-0.529	-0.455	-0.215		-0.491	-0.448	-0.0824
		*0.157****	*0.157****	*0.0575****		*0.172****	*0.159****	*0.0463**
share service		-0.626	-0.690	-0.380		-0.578	-0.646	-0.126
		*0.146****	*0.143****	*0.0575****		*0.156****	*0.147****	*0.0465****
share skilled manual		-0.327	-0.328	-0.329		-0.320	-0.297	-0.105
		*0.140***	*0.137***	*0.0556****		*0.152***	*0.139***	*0.0498***
share unskilled		-0.694	-0.660	-0.515		-0.625	-0.558	-0.112
		*0.143****	*0.144****	*0.0531****		*0.156****	*0.149****	*0.0461***
ownership (private=1)			0.0579	0.0299			0.0881	0.0525
			*0.0183****	*0.0172**			*0.0286****	*0.0262***
logL			0.0664	0.0152			0.0554	-0.0760
			*0.00821****	*0.00857**			*0.0101****	*0.0105****
year dummies	yes	yes	yes	yes	yes	yes	yes	yes
industry dummies	no	no	yes	yes	no	no	yes	yes
region dummies	no	no	yes	yes	no	no	yes	yes
Obs	76,576	76,576	75,882	75,882	76,599	76,599	75,906	75,906
R-squared	0.599	0.698	0.747	0.941	0.560	0.638	0.711	0.967

Standard errors in Italic, stars indicate significance levels: *p<0.1, **p<0.05, ***p<0.01. Standard errors are robust to firm-level clustering. Reference categories are as follows: share male, share primary school, share aged below 30, share professionals.

Table 1.17: Firm-level estimates (corresponding to Table 1.7)

	mean of individual wages				average wage bill			
	raw wage gap	individual controls	firm controls	firm FE	raw wage gap	individual controls	firm controls	firm FE
collective agreement	0.211	0.200	0.0390	0.0204	0.337	0.315	0.157	0.0682
	*0.0345****	*0.0233****	*0.0229**	*0.0139*	*0.0514****	*0.0408****	*0.0291****	*0.0109****
wage agreement	0.0700	0.0752	0.0549	0.0105	0.0652	0.0734	0.0571	0.00829
	*0.0299***	*0.0201****	*0.0222***	*0.00840*	*0.0418*	*0.0316***	*0.0266***	*0.00855*
share female		-0.153	-0.109	-0.0976		-0.193	-0.144	-0.0243
		*0.0399****	*0.0410****	*0.0284****		*0.0358****	*0.0380****	*0.0228*
share with degree		0.803	0.662	0.426		0.828	0.627	0.0795
		*0.0749****	*0.0730****	*0.0478****		*0.0752****	*0.0628****	*0.0327***
share with high school		0.398	0.287	0.0949		0.408	0.269	0.0113
		*0.0420****	*0.0342****	*0.0237****		*0.0473****	*0.0355****	*0.0149*
share aged 30-50		-0.0638	-0.00333	0.104		-0.185	-0.122	-0.0412
		0.0626	*0.0462*	*0.0440***		*0.0482****	*0.0392****	*0.0180***
share aged over 50		-0.00199	0.0726	0.129		-0.231	-0.154	-0.0913
		0.0600	*0.0470*	*0.0512***		*0.0615****	*0.0546****	*0.0223****
share managers		-0.324	-0.161	0.134		-0.876	-0.706	-0.176
		*0.142***	*0.139*	*0.0584***		*0.157****	*0.143****	*0.0545****
s. associate profess.		-0.313	-0.338	-0.125		-0.417	-0.510	-0.123
		*0.151***	*0.150***	*0.0717**		*0.175***	*0.161****	*0.0576***
s. skilled non-manual		-0.538	-0.449	-0.247		-0.531	-0.465	-0.136
		*0.160****	*0.160****	*0.0700****		*0.179****	*0.165****	*0.0664***
share service		-0.669	-0.726	-0.505		-0.640	-0.682	-0.166
		*0.148****	*0.147****	*0.114****		*0.161****	*0.150****	*0.0638****
share skilled manual		-0.332	-0.311	-0.342		-0.358	-0.303	-0.148
		*0.142***	*0.139***	*0.0656****		*0.159***	*0.145***	*0.0658***
share unskilled		-0.702	-0.654	-0.550		-0.663	-0.575	-0.162
		*0.145****	*0.146****	*0.0622****		*0.162****	*0.153****	*0.0631***
ownership (private=1)			0.0712	0.0364			0.106	0.0554
			*0.0204****	*0.0148***			*0.0304****	*0.0203****
logL			0.0600	0.00760			0.0494	-0.0791
			*0.00686****	*0.00963*			*0.00842****	*0.0108****
year dummies	yes	yes	yes	yes	yes	yes	yes	yes
industry dummies	no	no	yes	yes	no	no	yes	yes
region dummies	no	no	yes	yes	no	no	yes	yes
Obs	82,192	82,192	81,497	81,497	82,213	82,213	81,519	81,519
R-squared	0.614	0.716	0.760	0.942	0.581	0.663	0.730	0.969

Standard errors in Italic, stars indicate significance levels: *p<0.1, **p<0.05, ***p<0.01. Standard errors are robust to firm-level clustering. Reference categories are as follows: share male, share primary school, share aged below 30, share professionals.

Table 1.18: Firm-level estimates by period (corresponding to Table 1.8)

	mean of individual wages		average wage bill	
	individual and firm observables	firm FE	individual and firm observables	firm FE
wage agr * period 1	0.0811	0.0418	0.199	0.0864
	*0.0244****	*0.0110****	*0.0312****	*0.00970****
wage agr * period 2	0.0631	0.0149	0.190	0.0746
	*0.0178****	*0.0148*	*0.0251****	*0.0136****
share female	-0.0975	-0.109	-0.120	-0.0156
	*0.0367****	*0.0138****	*0.0358****	*0.0231*
share with degree	0.618	0.376	0.586	0.0447
	*0.0729****	*0.0436****	*0.0610****	*0.0338*
share with high school	0.279	0.105	0.248	0.00368
	*0.0319****	*0.0195****	*0.0347****	*0.0151*
share aged 30-50	-0.0168	0.0586	-0.132	-0.0313
	0.0429	*0.0161****	*0.0386****	*0.0182**
share aged over 50	0.0629	0.0811	-0.163	-0.0766
	0.0451	*0.0215****	*0.0552****	*0.0228****
share managers	0.519	0.181	-0.106	-0.124
	*0.0675****	*0.0492****	*0.0653*	*0.0362****
s. professionals	0.661		0.558	
	*0.144****		*0.149****	
s. associate profess.	0.342	-0.120	0.114	-0.0711
	*0.0517****	*0.0493***	*0.0717*	*0.0409**
s. skilled non-manual	0.206	-0.217	0.110	-0.0834
	*0.0498****	*0.0576****	*0.0733*	*0.0461**
share service	-0.0301	-0.382	-0.0882	-0.127
	0.0391	*0.0574****	*0.0586*	*0.0464****
share skilled manual	0.332	-0.330	0.261	-0.106
	*0.0321****	*0.0555****	*0.0502****	*0.0497***
share unskilled		-0.517		-0.113
		*0.0530****		*0.0458***
ownership (private=1)	0.0577	0.0303	0.0880	0.0527
	*0.0183****	*0.0174**	*0.0285****	*0.0263***
logL	0.0665	0.0139	0.0555	-0.0766
	*0.00820****	*0.00846*	*0.0101****	*0.0105****
year dummies	yes	yes	yes	yes
industry dummies	yes	yes	yes	yes
region dummies	yes	yes	yes	yes
Observations	75,882	75,882	75,906	75,906
R-squared	0.747	0.941	0.711	0.967

Standard errors in Italic, stars indicate significance levels: *p<0.1, **p<0.05, ***p<0.01. Standard errors are robust to firm-level clustering. Reference categories are as follows: share male, share primary school, share aged below 30, share professionals or share unskilled. Period 1 includes the years 1992-2000, period 2 includes the years 2001-2006.

Table 1.19: Firm-level estimates by the size of the firm (corresponding to Table 1.9)

	mean of individual wages		average wage bill	
	individual and firm observables	firm FE	individual and firm observables	firm FE
wage agr * size 1	0.152	0.0189	0.289	0.0235
	*0.0172****	*0.0118*	*0.0206****	*0.0111***
wage agr * size 2	0.0526	0.0318	0.171	0.0912
	*0.0211***	*0.0131***	*0.0311****	*0.0107****
share female	-0.0985	-0.108	-0.121	-0.0144
	*0.0366****	*0.0138****	*0.0358****	*0.0230*
share with degree	0.619	0.375	0.588	0.0433
	*0.0729****	*0.0436****	*0.0610****	*0.0337*
share with high school	0.281	0.104	0.251	0.00191
	*0.0318****	*0.0196****	*0.0346****	*0.0151*
share aged 30-50	-0.0169	0.0586	-0.132	-0.0316
	0.0429	*0.0161****	*0.0385****	*0.0182**
share aged over 50	0.0616	0.0817	-0.164	-0.0757
	0.0451	*0.0214****	*0.0554****	*0.0228****
share managers	-0.145	0.182	-0.668	-0.122
	0.137	*0.0492****	*0.137****	*0.0358****
s. associate profess.	-0.321	-0.118	-0.446	-0.0682
	*0.146***	*0.0494***	*0.154****	*0.0406**
s. skilled non-manual	-0.456	-0.215	-0.450	-0.0811
	*0.158****	*0.0575****	*0.159****	*0.0460**
share service	-0.695	-0.380	-0.651	-0.125
	*0.143****	*0.0575****	*0.147****	*0.0464****
share skilled manual	-0.330	-0.328	-0.299	-0.104
	*0.137***	*0.0555****	*0.139***	*0.0494***
share unskilled	-0.661	-0.515	-0.559	-0.111
	*0.144****	*0.0530****	*0.149****	*0.0457***
ownership (private=1)	0.0586	0.0296	0.0889	0.0512
	*0.0182****	*0.0173**	*0.0286****	*0.0255***
logL	0.0682	0.0148	0.0576	-0.0780
	*0.00855****	*0.00861**	*0.0106****	*0.0106****
year dummies	yes	yes	yes	yes
industry dummies	yes	yes	yes	yes
region dummies	yes	yes	yes	yes
Observations	75,882	75,882	75,906	75,906
R-squared	0.747	0.941	0.711	0.967

Standard errors in Italic, stars indicate significance levels: *p<0.1, **p<0.05, ***p<0.01. Standard errors are robust to firm-level clustering. Reference categories are as follows: share male, share primary school, share aged below 30, share professionals. Size 1 includes observations with less than 300 employees, size 2 refers to observations with less at least 300 employees.

Table 1.20: Individual estimates on separate samples by occupational category (blue-collar vs. white-collar, corresponding to Table 1.10)

	blue-collar			white-collar		
	individual and firm observables	**firm FE**	**WGFE**	**individual and firm observables**	**firm FE**	**WGFE**
wage agreement	0.0804	0.0381	0.0278	0.00858	0.0112	-0.00413
	0.00775***	0.00439***	0.00417***	0.0108	0.0105	0.0116
female	-0.185	-0.161		-0.108	-0.108	
	0.00626***	0.00257***		0.0112***	0.00397***	
degree	0.269	0.174		0.626	0.467	
	0.0177***	0.0111***		0.0139***	0.00885***	
high school	0.146	0.0848		0.205	0.132	
	0.00901***	0.00528***		0.0107***	0.00634***	
aged 30-50	0.106	0.104		0.160	0.210	
	0.00977***	0.00452***		0.0133***	0.00467***	
aged over 50	0.118	0.119		0.240	0.312	
	0.00923***	0.00493***		0.0128***	0.00577***	
ownership (private=1)	0.0720	0.0196	0.0222	0.0962	0.0854	0.0833
	0.00779***	0.00690***	0.00719***	0.0118***	0.0126***	0.0148***
logL	0.0617	0.0277	0.0324	0.0403	0.0120	0.00512
	0.00370***	0.00334***	0.00358***	0.00380***	0.00516**	0.00652
year summies	yes	yes	yes	yes	yes	yes
industry dummies	yes	yes	yes	yes	yes	yes
region dummies	yes	yes	yes	yes	yes	yes
Obs	727,942	727,942	727,942	480,847	480,847	480,847
R-squared	0.777	0.876	0.901	0.716	0.858	0.903

Standard errors in Italic, stars indicate significance levels: *p<0.1, **p<0.05, ***p<0.01. Standard errors are robust to firm-level clustering. Reference categories are as follows: male, primary school, aged below 30.

CHAPTER 2

2 Vintage Effects, Ageing and Productivity

(joint with Anna Lovász)

2.1 Introduction

The recent availability of longitudinal datasets that link employers to data on employee characteristics has enabled researchers to estimate not only the contribution of employer's decisions regarding capital, material inputs, and the size of their workforce to firm productivity, but also the role of skill endowment and the demographic composition of their workers. Several studies attempt to quantify the causal relationship between the age composition of firms' workforces and their productivity, mostly using data from western European countries and the United States[51]. Most of the results document a conventional hump – shaped age – productivity profile implying that prime aged workers are the most productive, and productivity declines with age (for example, Hellerstein and Neumark, 2004; Dostie, 2011; Vandenberghe, Waltenberg and Rigo, 2012).[52] The results showing a decline in older workers' productivity reflect one form of skill obsolescence[53]: the normal wear and atrophy of

[51] See for example the studies of Crepon et al (2002) on French data, Dostie (2011) on Canadian data, Ours and Stoeldraijer (2011) on Dutch data, Vandenberghe, Waltenberg and Rigo (2012) on Belgian data, Göbel and Zwick (2009) on German data, Hellerstein and Neumark (1999, 2004) and Haltiwanger et al (1999) on US data.
[52] However, some recent studies based on within-estimates suggest that the relationship between age and productivity is more ambiguous. For example, Ours and Stoeldraijer (2011) and Göbel and Zwick (2009) conclude that productivity does not decline with age.
[53] Skill obsolescence refers to certain skills becoming outmoded or obsolete. Alternatively, it can be thought of as a gap between the skills a worker needs to fulfill a job, and the skills the worker actually possesses. Rosen (1975)

skills associated with ageing that actually affects the workers' human capital, called *technical skill obsolescence*.

The relationship between ageing and productivity is also affected by another type of skill obsolescence called *economic skill obsolescence*, which is due to changes in jobs or the environment that lowers the value of the workers' human capital.[54] This affects specific cohorts of workers in addition to the normal wear of skills due to natural ageing. Rosen (1975) terms this a *vintage effect*, in that "stocks of knowledge available to society change from time to time [and] capital losses are imposed on those embodying the earlier knowledge and skills" (pp. 199-200). Though from a societal point of view these effects are not permanent since younger cohorts acquire new skills better suited to the market, they can have a significant detrimental effect on the labor market performance and activity of older workers, and the economy as a whole. Older workers experience a fall in demand for their labor and wage disadvantages. Sudden technological shocks will induce older workers to retire sooner (Bartel and Sicherman, 1993), placing a burden on government budgets. In ageing populations, the spreading of new technologies and growth may be hindered by the obsolescence of the skills of workers (Van Imhoff, 1988). At the same time, skill obsolescence is characteristic of current times, as production becomes increasingly knowledge intensive, and science and technology advance rapidly (Powell and Snellman 2004, David and Foray 2003). Thus, it is important to understand the roots and impact of economic skill obsolescence and the policy

is considered as the seminal work on measuring skill obsolescence and distinguishing among types. See De Grip and Van Loo (2002) for a review of the topic of skill obsolescence, its causes, and policy implications.

[54] A well-known example of this is the spread of computers in the workplace, which required new types of competencies and cognitive skills (Bresnahan et al, 2002).

tools that can alleviate its effects: continued adult training and a focus on giving students core competencies early on that enable easier lifelong learning.[55]

The economic transition in Hungary offers a unique opportunity to study the impact of economic skill obsolescence. The regime change led to a large-scale and sudden shock to the types of skills needed in the labor market than what is seen in developed countries. New technology and management practices were introduced rapidly requiring skills that were different from those needed under socialism. Prior to the transition, education emphasized technical as opposed to business-related skills, and work-based experience was also particular to the socialist system, often involving dealing with shortages, inconsistencies of plans, and transactions in a seller's market (Kertesi and Köllő, 2002). These skills quickly became useless as the economy opened up and market forces began to work. Based on empirical evidence on wages, this resulted in a sharp decline of returns to experience during the transition in Eastern European countries, especially among highly educated employees who acquired most of their knowledge and experience before transition.[56] This suggests that 20 years later, the Hungarian transitional experience gives us an opportunity for studying the impact of economic skill obsolescence and the adjustment process following a sudden shock to the value of skills. Our goal is to use the case of the Hungarian transition to assess the long-run effects of a shock to the value of older workers' skills, using data covering a long time period after the transition in 1990. We seek to determine how long the negative effect on older

[55] Mincer (1989) points out that in cases of sudden technological change firms have less incentive to retrain older workers, making government intervention even more crucial.

[56] Kertesi and Köllő (2002) documented that the experience-related wage gap narrowed significantly from 1992. The return to university education increased in general, but especially strongly among the younger cohorts, while the return to secondary education only increased among the young. Kézdi (2002) finds that return to skills increased, and the wage disadvantage of the young decreased compared to older workers, especially among the highly skilled. These changes in Hungary fit into the worldwide trend of skill – biased technological change, though it affected different sectors. Other studies on transitional countries focusing on the wage returns to experience and education mostly find decreasing returns to experience in the early years of transition. See for example, Rutkowski (1996) regarding Poland, or Vecernik (1995) on the Czech Republic.

workers' productivity lasted, and what the magnitude of the impact was. These lessons are useful not only for other transitional countries, but also for any country experiencing increases in foreign direct investment, skill-biased technological change, or any other vintage shock to the value of skills in their economy.

Rather than estimating wage returns and interpreting them as the extent of skill obsolescence, we focus directly on the effect of the changes on the relative productivity of older workers.[57] This allows more precise measurement, as wages may face downward barriers (such as collective agreements, minimum wage, deferred payment schemes, etc.) that mask the depreciation of skills. We adapt a methodology developed in previous international literature, and apply it to a large and representative dataset from Hungary covering a few years before the transition (1986) to almost 20 years after the transition (2008). The basis is the method pioneered by Hellerstein and Neumark (1999), which estimates a production function augmented with the workforce composition of the firm, as seen in most of the papers of the productivity and ageing literature cited above. This methodology allows us to estimate the productive contribution of various worker groups relative to a reference group at the firm level, using data on output, inputs, and various controls. The dataset used in the paper, the Hungarian Wage and Employment Survey (WES), is a nationally representative linked employer-employee dataset that includes detailed variables of a variety of firm characteristics, including the linked key demographic data of a random sample of workers from all firms with at least 20 employees.

[57] Kertesi and Köllő (2002), besides analyzing how the wage returns to experience and education changed after the transition, also estimate the firm-level productive contribution of older and younger workers differentiated by skill level for 1986-1999. Based on yearly OLS regressions, they document a widening productivity differential between young skilled and old skilled employees until 1999, the last year of their study. We build on their work using data from a longer time period, and more detailed and slightly different methodology.

The transitional environment and the nature of the skill obsolescence motivates investigating the old – young relative productivity using different specifications than applied in previous studies on western European countries and the United States. One implication of the model of economic skill obsolescence is that it should affect highly skilled workers to a larger extent than the low-skilled, since the material learned in elementary schooling does not change significantly over time (Neumann and Weiss, 1995). To verify this hypothesis, we investigate the productivity of older employees relative to the younger ones separately among skilled and unskilled employees. We define less aggregated worker groups than previous studies using the Hellerstein – Neumark methodology: our worker controls are composed of the interactions of education (with or without high school or college) and age (below or over 45). The older worker group is defined in an unconventional way – above the age of 45 – as this is better suited to the transitional analysis. [58]

A second testable implication is that if the value of skills changes due to a sudden shock in production technology or business practices (as opposed to natural ageing), then over time, skill obsolescence should play a less and less important role in influencing the productivity of older employees, as new cohorts of older workers acquire some of their skills in the post-transitional period. Besides expecting that the relative productivity of older employees varies by education level, we expect that, among skilled employees, the old – young productivity differential becomes smaller over time as new cohorts of older workers catch up, and acquire skills matching the needs of the market. On the other hand, we do not expect to see such a pattern among unskilled employees. To assess this hypothesis, we provide

[58] As Kertesi and Köllő (2002) notes, workers having 10-15 years work experience in the old regime already experienced the negative wage impacts of skill obsolescence. Following the productivity of the above 45 group over time means that we compare the productivity of a group in the first period with at least 15 years of work experience in the old regime, to a worker group in the consecutive periods who had more years to adapt to the new management and production practices after 1990.

estimates for five distinct time periods between 1986 and 2008, motivated by the major phases of economic development described in the next section.

Finally, the model implies that skill obsolescence should follow the inflow of modern capital. If the higher appreciation of the skills of the young was brought about by better matching to new technologies and practices, we would expect the old – young productivity differential to be larger in modern sectors and firms. Though we do not have information on firms' technologies and practices, previous studies suggest that foreign direct investment was the main channel through which modernization first occurred, so foreign ownership can be used to proxy the modern sector in the years following the transition (Kertesi and Köllő 2002, Kézdi 2002). Domestically owned private firms changed more slowly, so in terms of firm ownership, the adjustment cycle of first widening, then narrowing old-young productivity differentials should appear earlier on and be more pronounced in foreign-owned firms compared to domestic firms.[59] To assess the timing of the shock to skill value and the adjustment afterwards, we estimate the productivity differentials on subsamples of foreign, domestic, and state-owned firms separately.

The dataset allows us to estimate the augmented production functions using detailed data and the newest methods for addressing econometric issues. It provides us with further control variables describing the demographic composition of the firm (gender, occupation), and differences among firms that are due to industrial or regional variation. Since the dataset follows firms over time, we have the opportunity to identify the effect of older workers on firm productivity from within-firm (FE) variation in the share of older workers. Though

[59] Kertesi and Köllő (2002) proxy the "modern sector" using foreign firms for the period 1986-1999. Consistent with their expectations, the productivity differential among the skilled employees was higher in the "modern sector" already in 1990, and it started to widen in the domestic sector only a few years afterwards when modern technology appeared in those firms as well. They do not document any subsequent decrease in the gap up to 1999.

methods providing within-estimates are subject to many caveats as described in the literature,[60] the advantage of separating the productivity effect from the selection effect is important. This was not possible in most of the earlier studies estimating production function with information on worker composition, as they were usually carried out on a cross-section of the data.[61] Recently, there are some studies using panel databases and following firms over time, however, these databases tend to be less detailed regarding employee information (especially educational data), and shorter in time span than the database available to us.[62] Due to the likely measurement error issues that may bias the within-estimates towards zero, we interpret these estimates of the productivity differentials as a conservative estimate or lower bound of the true value. Since our data covers over 20 years, we are able to estimate the within-firm effects for separate time periods on large samples. Additionally, we address the simultaneity issue noted in the production function estimation literature by applying the structural method by Levinsohn and Petrin (2003).

Thus, our contribution is twofold. On the one hand, our paper contributes to the ageing and productivity literature based on the work of Hellerstein and Neumark (1999), by analyzing a country where the relative productivity of older workers may differ by education which necessitates the use of more detailed worker controls. Moreover, by having a long panel, we

[60] One of such problems is the measurement error, which may be especially relevant if the worker share variables are computed from samples. The downward bias caused by the sampling error may affect within-estimates more than OLS estimates. A detailed analysis about the likely magnitude of the bias and its relevance using different within methods is provided by Griliches and Mairesse (1995). The difficulties of obtaining within-estimates of worker shares are described in Haltiwanger, Lane and Spletzer (1999) and Hellerstein and Neumark (1998).
[61] There are several studies identifying the production function parameters using between-firm variation, e.g. Hellerstein, Neumark (1999, 2004), Hellerstein, Neumark and Troske (1999), Dostie (2011) or Van Biesebroeck (2007). The study by Kertesi and Köllő (2002) analyzing the wage and productivity returns to skill and experience after transition is also based on cross-sectional analysis.
[62] For example, Ours and Stoeldraijer (2011) uses a database of Dutch firms covering 2000-2005, and has information only on the age and gender of the employees. Crepon et al (2002) analyzes a French database of 1994-1997 including information on the gender, age and occupation of the workers. Borowczyk and Vandenberghe (2010) and Vandenberghe, Waltenberg and Rigo (2012) analyzes Belgian data covering the years of 1998-2006 and includes information on the gender, age and occupation of the employees. None of these studies has education data available.

can improve on earlier studies by assessing the changes in the relative productivities of older employees over five distinct time periods, which was never done previously. On the other hand, our paper contributes also to the literature on skill obsolescence. Using the Hungarian experience of a large-scale sudden shock to labor market skills in 1990, and estimating production functions for five distinct time periods, we can assess how economic skill obsolescence affected the older population on top of natural aging. We do this by applying the most recent econometric techniques handling both the firm-level heterogeneity and simultaneity issues, which was not possible in previous studies on the impacts of skill obsolescence. These lessons are useful not only for other transitional countries, but also for any country experiencing pervasive skill upgrading in their economy in the future.

In the remainder of the paper we will give an overview of the Hungarian transition, present our estimation method in detail, describe the data and sample used, and present our results for the full sample of firms and subsamples by ownership type. Our results confirm the implications of the economic skill obsolescence model, pointing to a vintage effect beyond natural ageing, and provide new information regarding the length of the adjustment process after such a shock. While the relative productivity of older workers is roughly constant across time within the unskilled, the results in the skilled category show that the productivity differential between the old and young employees increased sharply following the transition in 1990, then decreased over time to an insignificant value by 2006-2008. Among foreign firms, the old-young productivity differential for the skilled was largest immediately after the transition, while the differential among domestic firms followed a delayed pattern in line with the slower inflow of modern technology into that sector. Though the inclusion of firm fixed effects does not change these major conclusions, comparison with the OLS results suggest significant negative selection of older workers into less productive firms, and a significantly shorter and smaller impact of the regime change on the productivity of older skilled workers than implied by previous studies. The old-young productivity differentials obtained on samples after 2000 are comparable to those seen in Western European countries, and imply only a small or insignificant decline of productivity with age.

2.2 Empirical Methodology

2.2.1 Economic developments in Hungary 1986 – 2008

Before turning to the discussion of the empirical methodology, it is useful to get a brief overview of the economic developments in Hungary during 1986-2008. This analysis provides the basis for the division of our long time period into shorter subsamples in order to analyze how the old-young productivity gap evolved over time, and to lower the likelihood of structural breaks in the production function coefficients occurring within the time periods. Kertesi, Köllő (2002) and Kézdi (2002) yield a detailed analysis of the labor market developments in Hungary between 1986 and 1999, while the yearly issues of the Hungarian Labour Market,[63] and the comprehensive analysis of Ecostat (2010) gives an overview of the labor market and macroeconomic developments from 1990 until recently. Table 2.1 summarizes the basic economic indicators, such as the annual changes of GDP, export, import or the CPI, and Figures 2.1 and 2.2 show the evolution of activity and employment.

The early years after the regime change were characterized by a large scale job destruction, especially among the unskilled labor force. Real wages decreased for all types of

[63] See for example The Hungarian Labour Market – Review and Analysis 2005, eds: Károly Fazekas and Júlia Varga, and The Hungarian Labour Market – Review and Analysis 2009, eds: Károly Fazekas, Anna Lovász, Álmos Telegdy.

workers, with a widening wage gap between skilled and unskilled labor and a decreasing returns to experience.

As illustrated by Figure 2.1, the overall activity of the population decreased from its pre-transitional value of 5.4 million to 4.3 million by 1995. The drop in the employment numbers is even more pronounced: employment decreased from the pre-transitional value of 5.4 million to 3.6 million by 1995. The contracting employment possibilities affected the unskilled disproportionately: close to 90 percent of the jobs were lost by the least educated. Figure 2.2 gives a more detailed picture depicting the employment of the unskilled and skilled labor force separately. Among those with secondary school or higher education employment shrunk from its value of 1.8 million in 1990 to 1.6 million by 1995, while the number of unskilled employees dropped from 3 million in 1990 to 1.9 million by 1995. Regarding the other economic indicators, the early years of the transition from 1990 until 1995 are characterized by first sharply falling and then slightly increasing GDP, high inflation, and large current account imbalances.

In 1995 the government introduced a stabilization program including fiscal restrictions and changes in monetary policy. The years from 1995 until 2000 - 2001 can be characterized as a period of stabilization and recovery and growth, with an annual GDP growth exceeding 4 percent each year from 1997 until 2000. Regarding the labor market developments after 1995, new jobs were created, but only among the skilled labor force. Real wages also started to rise at the upper tail of the wage distribution. Between 1995 and 1999 skill premium increased steadily, but only among the young. As Kézdi (2002) argues, the early years of transition were characterized by between-industry reallocation, while changes after 1995 can be considered as a result of skill-biased technological change.

Since 2000, the aggregate numbers of activity and employment showed only minor fluctuations and stabilized at a relatively low level. The more detailed analysis by educational groups reveals that the employment possibilities for the unskilled decreased further, while the number of skilled employees slightly rose. The growth rate of the GDP experienced only a minor decrease in 2001-2003, and it was around 4 percent in 2004-2006. Real wages continued to increase until 2006. The government introduced fiscal restrictions in 2006 as a consequence of the unsustainable governmental spending. Both the growth rate of GDP and of real wages decreased from 2006, but the fiscal restrictions did not have yet a large impact on the aggregate activity and employment level.

Based on the main phases of the economic development described in previous papers and macroeconomic analysis, we divide our sample into five periods. The first period covers the years 1986 and 1989 prior to the transition. The next period includes the years of post-transitional recession, 1992-1995, during which employment fell sharply, especially among the unskilled. The consequent period of recovery and growth between 1996-2000 comprises the third period. The fourth is characterized by growing macroeconomic imbalances, and includes the years from before the EU accession and the accession itself, 2001-2005. The final period covers the years of fiscal consolidation, which started in 2006, and these years are already the early stages of the onset of the economic crisis.

2.2.2 Specification of the augmented production function

In order to measure the effect on older workers of the changes in job skill requirements as a result of the sudden inflow of modern technology and practices seen in the transition, we focus directly on their relative productive contribution compared to younger workers. This provides a more direct measure of the impact than wage differentials, which may be constrained by other factors. We assess the productivity of worker groups over five time periods between 1986 and 2008, so we are able to observe the effects of the changes in the longer run. At a given point in time, the gap between old and young workers arises as a combination of technical skill obsolescence (natural deterioration that affects human capital) and economic obsolescence (changes outside the worker that affect the skills needed for production). However, comparing the productivity differential over time, we can assume that sudden changes are due to the latter type of obsolescence, since we expect that the disadvantage of older workers that is due to ageing alone should be relatively stable over time.

To assess the relative contributions of different age and education groups to the production of firms, we estimate a production function at the firm level taking into account the demographic composition of the firm. The approach originates from Griliches (1957) and was later pioneered by Hellerstein and Neumark (1999). Our empirical analysis uses the following variant of the Cobb-Douglas production function:

$$\ln VA_{jt} = \beta_0 + \beta_1 \cdot \ln K_{jt} + \beta_2 \cdot \ln L_{jt} + \sum_k \gamma_k \cdot l_{k_{jt}} + \lambda \cdot X_{jt} + \varepsilon_{jt} \qquad (1)$$

Equation (1) includes on the left hand side the logarithm of value added as the output measure, while the right hand side variables are the logarithms of capital and employment denoted by ln*K* and ln*L*, and the l_k worker shares defined as the proportion of workers in group *k* within the labor force of the firm. Unlike Hellerstein and Neumark (1999), we estimate the production function in linear form. Thus, in our paper, the estimated group share coefficients cannot be directly interpreted as relative productivities, they can be simply thought of as the contribution to value added output of the different worker groups. More precisely, the γ_k coefficients can be considered roughly as elasticities: if l_k, the share of workers in group *k* within the firm increases by 1 percentage point, value added changes by γ_k percent. Throughout the paper, when we discuss the productivity of the different worker groups, we are referring to the estimated γ_k parameters.[64]

We first estimate a simplified model to assess the young-old differential overall, which we refer to as the *restricted model*. The worker groups and corresponding l_k worker share variables are defined as follows: female workers, workers aged over 45, and workers with higher education (as well as broad occupational categories in robustness checks).[65] We chose age 45 as the lower bound for the older worker category as it is better suited to the transitional analysis than the conventional age bound of 50. As suggested by previous studies (Kertesi and Köllő 2002, Kézdi 2002), the transition-related skill obsolescence affected not only the oldest generation, but all those with at least 15 years of work experience in the old regime[66]. Higher education is defined as having completed college or high school, as the largest wage gaps have been documented between vocational and high school education levels in previous studies.[67] The productive contribution of each of these groups is estimated relative to their reference group (males, aged under 45, and no higher education). The equation also includes controls for time, industry, region, and ownership effects summarized by the matrix X.[68] The underlying assumptions behind the restricted model are that the relative productivity of each group is

[64] Chapter 3 of the thesis gives a more detailed overview of the model and assumptions underlying the estimated equations.
[65] When included as additional controls, the seven occupational categories are defined based on the first digit of the Hungarian occupational code (FEOR). However, we will present the results of the specifications with no occupational shares, as the inclusion of controls that are themselves dependent on education/age may bias the estimates (Angrist and Pischke, 2009). The overall trends regarding education and age do not differ significantly in either case, though there is significant evidence of occupational level selection. The between and within firm results with occupational shares included can be seen in Appendix Tables 2.16. – 2.19.
[66] Kertesi and Köllő (2002) defines “old” as having experience more than the median years of work experience, which was 21 years.
[67] Kertesi and Köllő (2002) document the gap between wages of workers with these two education levels. We also carry out the estimation with higher education defined as college only. The results show very similar overall trends, and are presented in Appendix Tables 2.12. – 2.15.
[68] We control for the interaction of 19 industrial categories and year dummies, 7 regions, and ownership.

constant across all other categories (for example, the gender productivity differential is the same among older and younger employees), and that the proportion of each group is constant across all other categories (for example, the proportion of female employees is the same in each age category).

There is good reason to believe that the above restrictions may be invalid, and some previous studies partially relax the restrictions to allow the effects to differ between more detailed groups.[69] As our goal is to study changes in the value of skills after the transition, we relax the assumption regarding age and education level to get more detailed results for our groups of interest, and allow for the case that older workers who are highly educated fared differently following the transition than those with lower levels of education. We do not relax the restriction on gender (or occupation when included), but leave these shares in the estimated equation as controls. We are left with the following worker group cells: female or male, educated above 45, educated below 45, uneducated above 45, or uneducated below 45, (white collar, manager). The coefficient estimates of interest with respect to our hypotheses are: the estimated productive contribution of the educated above 45 relative to the educated below 45 group, and that of the uneducated above 45 group relative to the uneducated below 45 group.[70] We refer to this specification as the *partially unrestricted model*.

[69] For example, Hellerstein and Neumark (2004) relax the equal relative productivity assumption regarding marriage, race and gender. They refer to empirical evidence that the marriage wage premium and the race differential are larger for men than for women. Note, however, that estimating an unrestricted model may require estimating a large number of parameters. Overly detailed worker group cells pose a problem, since the firm level worker shares are usually calculated from a sample of workers linked to each firm, not the full workforce. This introduces measurement error in the worker shares, which may bias the within estimates much more than the OLS estimates, thus there is a trade-off between the number of worker groups and the precision of the estimates.
[70] Note that our regressions results in the Appendix show only the estimates with respect to one chosen reference category (with respect to young skilled as the reference category). However, the coefficient estimates of interests presented in Table 2.7 (old skilled to young skilled, and old unskilled to young unskilled) can be simply computed from these numbers.

We estimate the trends in productivity for the five periods described in the previous section, and separately by firm ownership type, in line with the hypothesis that the higher productivity of skilled young employees can be explained by their skills being better matched with the new technology, which was first present in foreign-owned firms. Firms are classified as *foreign* if they are majority foreign-owned and *domestic* if majority domestic private-owned. The final category of ownership is *state* owned, defined as those firms that were never privately owned. These categories allow us to compare the relative productivity of older workers for the periods after 1990. In order to show that any gap in productivity resulted from skill obsolescence due to the inflow of modern technology and production practices, we would need to have an estimate of the old-young productivity differential prior to the change on the foreign and domestic subsamples. However, prior to 1990, all firms in Hungary were state-owned, so we do not observe any foreign or domestic firms in the first period. We approximate the relative productivity of older workers in foreign (domestic) firms before the transition (1986-1989) by estimating on the sample of firms in the first period that later became foreign (domestic), i.e. the state-owned firms that were later privatized.[71] These estimates cannot be regarded accurate, as firms in the later periods may also have been new entrants or split-up successors of large pre-transitional firms, which are not necessarily linked to their predecessors. However, these estimates give us some idea of the nature of the old-young productivity gap prior to the changes.

[71] The subsample of later foreign-owned firms in the first period is very small (182), while the number of foreign-owned firms is significantly higher in the second period (1655). This suggests that (a) many foreign firms were new entrants to the market after 1990, and (b) we may not be linking all privatized firms to their predecessors in the dataset. The latter may be due to cases when a single firm was broken up into several successors, and only a single successor is linked to the predecessor. Among the 1,655 majority foreign owned firm observations in the second period, we have found 590 cases with positive level of state ownership, which indicates that these firms probably existed already before 1990, but we cannot observe them in those years. Due to these problems the first period results for future foreign-owned firms should be interpreted with these caveats in mind. In case of the future domestic-owned firms the number of observations is much higher in the first period (3,224 firm-years).

2.2.3 Estimation methods and potential biases

The estimation of production functions involves several econometric problems. Among them, researchers pay the most attention to controlling for unobserved heterogeneity and tackling the simultaneity between the input-output choices. Starting with the simplest way to estimate the production function, we use alternative procedures to correct the above mentioned problems. In our baseline specification, we estimate equation (1) for each time period via OLS. In this case, the parameter estimates are identified by cross-sectional variation. However, it is possible that some of the observed productivity differential is due to the selection of workers into better (high productivity) or worse (low productivity) firms. To separate observed productive differences into the part that is due to selection of workers into good or bad firms and productivity differences within firms, we run the same regressions including firm fixed effects.[72]

Another challenge inherent in production function estimation is to tackle the endogeneity bias caused by unobserved productivity shocks. One way to overcome the bias is to use instrumental variables. The most common candidates to instrument the current values of the inputs are the lagged values of the variables, however, these instruments are often considered to be weak.[73] An alternative way to deal with the endogeneity issue is a structural approach proposed by Olley and Pakes (1996) and developed further by Levinsohn and Petrin

[72] Although our data allows us to control for firm fixed effects, as Haltiwanger, Lane and Spletzer (1999 and 2007) point out its identification difficulties due to the small within-firm variation of the group shares. They draw the attention to the stylized fact that labor productivity, earnings per worker and workforce composition are quite heterogeneous across firms and quite persistent within firms. In our data we also find considerable persistence in the worker composition of the firms, suggesting that the fixed effects results should be interpreted as lower-bound estimates. The first order AR coefficient for the ratio of college graduates regressing the 1996 on its 1992 value is 0.69 after removing industry means. The same coefficient for workers above 40 is 0.50.

[73] See, for example, Aubert and Crepon (2006); Ours and Stoeldraijer (2011).

(Levinsohn and Petrin, 2003; henceforth LP) and Ackerberg, Caves and Frazer (Ackerberg, Caves and Frazer 2006, henceforth ACF).[74] As our aim is to compare how the productive contributions of various groups change over time, we follow the structural approach to avoid the loss of observations that occurs when using lags as instruments. First we apply the LP method using cross-sectional data as was usually done in previous studies[75]. Additionally, we also provide estimates taking care of both unobserved firm heterogeneity and time variant productivity shocks. This was rarely done in previous literature[76].

Thus, our preferred specification taking care of both firm fixed effects and unobserved productivity shocks in all subsamples will be the LP+FE method, but we provide estimates using several methods. First, we estimate the production functions for all periods and subsamples via OLS. Next, we include the "LP term" into the production function. The third specification includes firm fixed effects without the "LP term", while the fourth set of results are produced including both firm fixed effects and the "LP term".

Finally, a further potential bias should be kept in mind when interpreting our results regarding the old-young productivity differentials. During the fall in employment following the transition, the composition of the workforce changed, which may affect our results. It is possible that labor market selection (better old workers remain in labor market) biases the gap

[74] Hellerstein and Neumark (2004), Dostie (2011), Vandenberghe (2011), Vandenberghe, Waltenberg and Rigo (2012) all apply structural methods to correct for biases.
[75] For example Hellerstein and Neumark (2004) and Dostie (2011).
[76] Vandenberghe (2011) applies the combination of LP and firm-fixed effects to estimate the impact of ageing on productivity and wages by gender in Belgium. Technically, LP estimates the production function in the first stage including the "LP term", which is a function of material cost and capital, approximated with a third order polynomial. Separating the original error term u_{jt} into an unobserved productivity component ω_{jt} and a pure noise parameter e_{jt}, consistent estimates of the labor terms can be obtained in the first stage by estimating: $\ln VA_{it} = \gamma \cdot \ln QL_{jt} + \sum_{p=0}^{3}\sum_{q=0}^{3-p} \varepsilon_{pq} \cdot (\ln K_{jt})^{p} (\ln M_{jt})^{q} + \delta \cdot Z_{jt} + e_{jt}$ where the polynomial term is a third-order Taylor approximation of the expression: $\phi_t(\ln K_{jt}, \ln M_{jt}) = \beta_0 + \alpha \ln K_{jt} + g(\ln K_{jt} \ln M_{jt})$. The function $g(.)$ is used to proxy the unobserved productivity component. Combining the LP method with firm fixed effects means estimating the first-stage regression on demeaned variables.

estimate, if the older workers remaining in the labor force differ on average from those who left. However, since we can assume that older workers who remained in the market were "better," more productive workers, the bias should lead us to underestimate the old-young gap, which means that any significant gap (or increase in the gap) between the old and young is even stronger evidence of economic skill obsolescence.

2.3 Data and Sample

The Hungarian Wage and Employment Survey is available from the National Employment Office for the years 1986, 1989, and 1992-2008. The sample frame includes all full time workers from tax-paying legal entities with double-sided balance sheets that employed at least 20 employees in 1986, extended to firms with at least 10 workers in 1995, and from 1999 on to micro-firms as well. To ensure comparability over all years of the data, all key variables have been harmonized, and we limit the sample to firms with at least 20 employees. Only firms from the enterprise sector are included. In 1986 and 1989 a random sample of workers was drawn based on the full set of employee names: every 5th production worker and every 7th non-production worker was chosen. Starting from 1992, workers from each firm were selected into the sample based on their date of birth: production workers were included if their birth date fell on either the 5th or the 15th of any month, and non-production workers if it fell on the 5th, 10th, or 15th of a month. Sampling weights are provided to ensure a representative sample of the two worker types.

The WES includes demographic information for this random sample of workers, matched to the detailed characteristics and balance sheet information of the firms where they are employed. Worker variables include the gender, age, highest completed education level (five categories: less than 8th grade, elementary, high school, vocational, university), and occupation (4 digit occupational code). For the purposes of determining the various worker group cells, we define the two age categories (under 45, over 45), two education categories (college or high school, no college or high school), and also use gender. When estimating the specification including occupation as a robustness check, we define seven broad categories. The worker level data is used to calculate the shares of each worker group cell of the restricted and partially unrestricted specifications within each firm for each year. These firm level worker shares are then linked to the employer dataset for the estimation. The firm variables included in the production function (in real terms) are the firms' value added output, capital, material cost, and employment taken from the company's reported Tax Authority data, as well as controls for industry (12 categories based on the 4 digit ISIC standard classification code, interacted with year dummies), region (7 regions as defined by the CSO), and ownership (majority foreign, domestic, or state).

The sample is further restricted due to the nature of the worker share calculation and production function estimation. In order to have a reasonable number of observations of employees within each worker group cell, and to minimize measurement error in the shares, we include only firm years in which at least 5 workers from the workforce are sampled in the linked employee data. The resulting database includes observations on 102,270 firm-years and 31,607 unique firms. Tables 2.2. and 2.3. give the summary statistics of the firm-level variables and the calculated firm-level worker shares for the five time periods between 1986 and 2008. The firm balance sheet variables show trends familiar from transitional literature: mean value added output, capital, and employment decreased sharply after 1990 as large state enterprises were privatized and broken up, and new firms entered. In the long-run, value added output eventually increased by the last time period (2006-2008), while capital and employment continued to decrease steadily. The worker share variables reflect significant differences across the time periods. The share of workers over 45 increased from 0.31 in the first period to 0.39 in the fifth, while the share of highly educated workers rose significantly from 0.28 to 0.50. The share of educated young workers increased from 0.22 to 0.32, while that of educated older workers rose from 0.06 to 0.18. The share of uneducated younger workers fell from 0.25 to 0.21, and the share of uneducated older workers fell more significantly from 0.47 to 0.29.

Tables 2.4. and 2.5. give the mean firm level statistics for the subsamples of foreign, domestic private, and state-owned firms. In the first period, there are no foreign and domestic private firms, and as their number rises sharply from the second period, the number of observations of state-owned firms decreases. The firm balance sheet information confirms that these types of firms are significantly different. Value added and capital are about four times as high in foreign as in domestic private firms, while for state-owned firms they were very high initially, but decreased steadily. In terms of employment, foreign-owned firms are significantly larger than domestic private firms on average, and state-owned decreased over time in size. Comparing the workforce composition variables between the two types of firms, foreign firms tend to have a significantly more educated and younger workforce than domestic firms. The ratio of workers over 45 is lower at foreign firms (around 0.3), while it is higher and increasing among domestic private (from 0.33 to 0.4) and state-owned (from 0.31 to 0.53) firms. The share of educated workers was lowest at state-owned firms but increased (from 0.29 to 0.5), and highest at foreign firms (0.46 to 0.57). In the more detailed categories, the group most affected by economic skill obsolescence – educated older workers – employment was highest in state-owned firms, while the ratio of educated younger workers is significantly higher in foreign firms, reaching 0.43 in 2006-2008.

2.4 Results

We now turn our attention to the relevant productivity coefficient estimates for the five time periods following the transition. First, we briefly discuss the restricted results focusing on the two main worker groups – workers over 45 and educated workers - separately, reviewing the average trends over time. These are compared to international results from studies employing the same production function-based methodology. We then focus on the estimates in the partially unrestricted case in which we estimate productivity effects for interactions of education and age, allowing the old-young productivity gap to differ by education level. As the inclusion of the LP term did not have a large impact on the magnitude of our estimates, and the trends are not affected, we will mostly limit the discussion on the starting OLS and the final FE+LP specifications. The results including the coefficients of interests are presented in Tables 2.6 and 2.7, while the full set of estimated coefficients are in Tables 2.8 – 2.19. in the Appendix.

2.4.1 Restricted specification: age and education effects

The majority of previous international studies on the productivity effects of ageing find that a higher proportion of old employees is associated with lower productivity.[77] Table 2.6

[77] Hellerstein and Neumark (2004) using cross-sectional data find that old employees are less productive, with a relative productivity of 0.79. Haltiwanger, Lane and Spletzer (1999) and Lallemand and Rycx (2009) examining the relationship between labor productivity and the age composition of the firm, also find that older workers

presents the restricted production function results for Hungary in the five time periods between 1992 and 2008. Our results regarding age effects are mostly in line with estimates obtained in the literature: we estimate that the share of workers above 45 is negatively associated with firm-level productivity, especially in the OLS specification. The estimates suggest that before the regime change a percentage point increase in the share of older employees decreased firm output by about 0.26 percent. In the first two periods of the transition, from 1992 until 2000, the negative impact became more pronounced (-0.33 and -0.4), and the old-young productivity gap decreased after 2001 (-0.23 and -0.25 in the final two periods). The within firm (FE+LP) estimates, interpreted as lower bound estimates, suggest a significant negative effect of -0.095 percent only in the period right after the regime change. While OLS results imply that above 45 workers are less productive than younger employees even in the last period of our study, the within estimates suggest that older workers are non-randomly selected by less productive companies, and within firms, the old-young productivity gap decreased to insignificant over time. This is in line with our hypothesis that economic skill obsolescence resulting from a shock to the value of skills plays a less and less important role as new cohorts acquire skills that are better suited to modern production.

As expected, previous empirical results point to a positive association between productivity and the ratio of workers with higher education within firms.[78] We see this confirmed in the Hungarian results, though within firms, the estimates are only significant in

decrease productivity. Vandenberghe, Waltenberg and Rigo (2012) using Belgian data and applying within specification, estimate that a 10 percent increase in the share of older workers (50-64 years) decreases firm productivity by around 2 percent. However, Ours and Stoeldraijer (2011) using Dutch data, and Göbel and Zwick (2009) on German data conclude that productivity does not decrease with age in their within specifications. The empirical result is similar in Sweden: Malmberg et al (2005) find that the lower productivity of older workers reflects that older workers tend to be employed in firms with less efficient technologies.

[78] Hellerstein and Neumark (2004) estimate a 56 percent productivity premium for a diploma. Haltiwanger, Lane and Spletzer (1999) also estimate a positive relationship between firm-level productivity and the proportion of workers with college education.

the period of 2001-2005. OLS results suggest that a one percentage point increase in the share of educated (defined as high school or college) employees increased the value added output of firms by 0.92 percent before the regime change, which increases to 1.1 – 1.3 after 1990.[79] The FE+LP within-firm results suggest an insignificant negative effect of 7 percent initially, which increased to a significant 7 percent by 2001-2005. Firm-level selection plays a crucial role in determining the observed productivity differences between educated and less educated employees.

Though the restricted model is indicative of changes in the relative productivity of different worker groups in line with the less and less important role of skill obsolescence, it cannot answer some of the questions, which were necessary to underline our hypothesis. For example, does the insignificant productivity gap (FE+LP) between skilled and unskilled workers reflect the drop in the productivity of older skilled workers after the regime change? Alternatively, does the increasing relative productivity of skilled workers (especially in the within specifications) reflect improvement in all age categories, or perhaps it is to some extent due to the educated old category being more productive over time? Or, though the restricted estimates suggest that older workers improved their productivity over time, it would be interesting to see if there are differences in the relative productivity of older workers by education, which is actually predicted by the skill obsolescence phenomenon. In the next section we turn to presenting estimates of the partially unrestricted model.

[79] This increase is in line with the results of Kertesi and Köllő (2002) covering the years up to 1999.

2.4.2 Partially unrestricted results – age effects by education level

Estimation results of the partially unrestricted model confirm that it is useful to group workers into more detailed categories defined by the interaction of age and education. The OLS and FE+LP estimation results for the five periods are presented in Table 2.7.[80] The estimated relative productivities of skilled and unskilled workers over 45 are shown both for the full sample of firms, and separately for the subsamples of foreign, domestic, and state-owned firms. A comparison of the OLS and FE+LP results confirms the significant role of firm-level negative selection of older workers: the old-young gap is significantly smaller in magnitude, showing a smaller disadvantage for older workers, within firms. The overall trends point to the same conclusions regarding the main hypotheses of the economic skill obsolescence model in both the OLS and FE+LP cases. We find evidence of a significant impact of the inflow of modern technology on the labor market position of older workers through the decrease in the value of skills gained prior to the transition. We also find evidence of a long-run adjustment process: fifteen years after the transition, the skill set of the workforce has sufficiently adjusted to return to a productivity-age profile that is similar to that documented in western countries.[81]

The results obtained on the full sample of firms show a higher productivity differential in the skilled than in the unskilled group - with the exception of the first period prior to the transition – and a large rise in the gap following the transition that fades over time. The OLS

[80] As the inclusion of the LP term did not have a large impact on the estimates, we only present our starting OLS and the final FE+LP specification results here. The full set of estimation results in the OLS and FE+LP specifications, as well as the estimates including occupation and using college degree to define the skilled group, are included in Appendix., Tables 2.8. – 2.19.

[81] Our results of insignificant productivity gap in the within specifications between older and younger employees by the last period of the study is in line with the findings of Ours and Stoledraijer (2011) and Göbel and Zwick (2009). Both studies document an insignificant decrease of productivity with age in the within specification. Vandenberghe, Waltenberg and Rigo (2012) finds a small significant decrease of productivity with age.

estimate of the gap for educated older workers is not significantly different from zero before the transition, then a significant -0.48 in 1992-1995, highest in magnitude at -0.65 in 1996-2000, and the gap is smaller in the last two periods. The FE+LP results show no significant gap in the first two periods, significant gaps of -0.13 in the third and -0.1 in the fourth periods, before becoming insignificant again in the fifth. Unskilled older workers, on the other hand, were relatively less productive than younger workers in the initial period before the transition, after which the gap decreased and leveled out in both the OLS (at around -0.23) and in the FE+LP (around zero) estimates. Based on the ownership subsample results, the initial significant negative gap among the unskilled is mainly due to the firms that are always state-owned (never privatized). Overall, there is no significant decrease in the relative productivity of unskilled older workers after the transition as is seen among educated older workers. This suggests that the inflow of modern technologies and production methods affected the value of the skills of educated workers more than those of unskilled workers. This is in line with the skill obsolescence model implying that it is the material taught in higher education that is especially subject to be rendered useless due to sudden shocks, while elementary school material changes more slowly.

Separate estimates by ownership are strongly indicative that the devaluation of skills is related to the inflow of modern capital. In the sample of foreign-owned firms, the productivity differential among educated older workers is largest in the second period of 1992-1995, showing that a one percentage point increase in the share of older educated workers decreases value added by -0.96 percent in the OLS, and by-0.6 percent in the within-firm (FE+LP) case. The gap then gradually decreases: to -0.79, -0.29, and finally insignificant in the OLS, and to insignificant in all subsequent periods in the FE+LP specification. To see whether this large negative gap resulted from the changes due to modernization, we have to rely on the results using the subsample of firms in the first period that are later foreign-owned. The OLS estimate shows an insignificant negative old-young gap, and the FE+LP estimate is positive and insignificant. Though these results are estimated with large standard errors, probably due to the issues described earlier – that we observe only privatized firms, not new entrants, and the small number of observations – they suggest that prior to privatization, older workers were not negatively correlated with firm output. Among unskilled older workers, we do not see a significant gap in the OLS estimates, while the within-firm estimate is significant and negative in the second period immediately after the transition. The magnitude of the drop is smaller than what we see among the highly skilled, in line with our expectations. Overall, we can see the immediate effect of economic skill obsolescence in the foreign firm sample.

The results of the domestic private subsample of firms show a delayed effect compared to foreign firms, in line with a slower adoption of modern technology and production practices. For skilled workers, there is no significant old-young gap in the first period (estimated on the sample of firms that later become domestic private) in either the OLS or the FE+LP case. The gap begins to increase in the second period in the OLS case (-0.44), but reaches its highest in the third period (-0.63), before decreasing to around -0.21. In the FE+LP case, there is no significant gap until the third period (-0.18), then a gradual decrease to zero by 2006. The magnitude of the negative effect is smaller than seen in foreign firms, but the negative impact lasted somewhat longer than in the foreign sample as implied by the FE+LP results. Unskilled older workers were not significantly impacted by economic skill obsolescence due to modernization in domestic firms. The OLS results remain relatively stable around a significant gap of -0.2 to -0.3, while the FE+LP results show no significant old-young gap among the unskilled in any period.

The results estimated on the subsample of always state-owned firms do not reflect a disadvantage of older skilled workers, with insignificant OLS and FE+LP gap estimates in most periods, and no drop following the transition. The OLS results show a significant positive gap in the fourth period, but this disappears in the within-firm case. Overall, the fact that we do not see any evidence of a gap during the periods following the transition supports the implication that the changing value of skills occurred as a result of modernization that took place first in foreign, and later in domestic private firms.

Overall, our findings strongly support the implications of the model of economic skill obsolescence regarding the effects on older workers' productivity following a sudden shock in technology and management practices. In the long-run, skill obsolescence plays less and less important role, but based on our results it takes roughly 10 years for older workers to improve their relative productivity (i.e. for the skill set of the older age group to become better suited) to a level than seen in western European countries nowadays.[82] The within estimates imply that the catching up of older workers took less time than predicted by the OLS results, though the FE results have to be interpreted with special care due to the likely downward bias of the estimates caused by measurement error. The Hungarian experience shows that this adjustment phase comes at a high cost through the mass discouragement of older cohorts and its effect on the labor market and economy.

[82] For example, OLS estimates of production function on Belgian data (Vandenberghe, Waltenberg and Rigo, 2012) imply a productivity coefficient for workers over 50 relative to prime age workers of -0.315. On Dutch data (Ours and Stoeldraijer, 2011), the productivity coefficients of workers over 45 relative to prime age workers lie between -0.27 and -0.37 in the OLS specification. Neither Ours and Stoeldraijer (2011) nor Göbel and Zwick (2009) found a significant decrease of productivity with age in their within specifications, and the FE results on the Belgian data show a coefficient estimate on the relative productivity of old employees relative to the prime age category of -0.242.

2.5 Conclusion

In this paper, we use a linked employer-employee dataset from Hungary covering the years of 1986-2008 to assess the evolution of relative productivities of various age and education groups over time. During this period, Hungary underwent a rapid economic transition, and joined the European Union, which significantly impacted production processes and technologies. Based on a model of economic skill obsolescence where the value of workers' skills decreases due to a change in the job environment, we study whether the old-young productivity gap was larger among the highly skilled, the magnitude and length of the impact, and its evolution among different ownership types reflecting the inflow of modern capital. We estimate the relative productivity of educated (high school or college graduates) and unskilled workers over the age of 45 compared to younger workers based on an augmented production function. We estimate these using OLS, by applying the structural method by Levinsohn and Petrin (2003), as well as using firm fixed effects specification (also with combination of the structural method) over five distinct time periods reflecting major phases of the transition and subsequent years. We carry out the estimation on the full sample of firms, as well as on the subsamples of majority foreign-owned, domestic-owned, and state-owned firms.

The results reflect a vintage effect due to the changes in the value of skills that is beyond the disadvantage of older workers due to normal wear and atrophy of skills documented in previous studies on non-transitional countries. Educated older workers became relatively less productive compared to the young first in foreign-owned firms in 1992-1995 (a gap of -0.6 within firms), then later in domestic firms in 1996-2000 (a gap of -0.18 within firms). No such decrease was seen in private sector firms that remained under state ownership.

The old-young gap among educated workers decreased back to an insignificant level by the final period in 2006-2008, as newer cohorts with better suited skills replaced workers in the older age group. We do not see such a significant negative effect on the situation of unskilled older workers, suggesting that the content of lower-level education did not become suddenly outdated as that of higher level education and job experience. The pattern of the appearance and subsequent decrease of the old-young productivity differential among different firm ownership types gives strong evidence that the change in value of skills (and productivity of workers) resulted from the inflow of modern technology and management practices, which first took place in foreign, and later in domestic private firms.

Our results based on within-firm estimates are indicative that the speed of adaptation of older workers to the modern technology was probably faster than implied by previous studies (Kertesi and Köllő, 2002). By the last period, roughly fifteen years after the transition, the old – young relative productivity coefficients are comparable to those found in previous studies on western European and U.S. data, documenting an insignificant or small decrease in productivity for older age groups. However, the cost of this period of adjustment can be seen in the lower productivity of older workers, the fall in their relative wages and employment, and the consequent high rate of inactivity in Hungary during the time period. Thus, the results of our research highlight the importance of policy steps that are aimed at decreasing the impact of economic skill obsolescence: continual adult education to help older workers keep their skill sets valuable, especially among educated workers who are the most affected, and teaching of core competencies at all education levels that enable workers to adapt by learning new skills more easily. These lessons are not limited to countries experiencing an economic transition, but to any situation where skill obsolescence of this type may arise through technological change or foreign investment.

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2.7 Tables and Figures

Table 2.1: Basic economic indicators

Year	*GDP**	*Industrial produc-tion**	*Export*	*Import*	*balance of current account / GDP*	*Real earnings**	*Employ-ment**	*Consumer price index**	*Unemploy-ment rate*
1989	100.7	95	100.3	101.1	…	99.7	98.2	117	…
1990	96.5	90.7	95.9	94.8	+0.4	94.3	97.2	128.9	…
1991	88.1	81.6	95.1	105.5	+0.8	93	92.6	135	…
1992	96.9	84.2	101	92.4	+0.9	98.6	90.3	123	9.8
1993	99.4	103.9	86.9	120.9	–9.0	96.1	93.8	122.5	11.9
1994	102.9	109.7	116.6	114.5	–9.4	107.2	98	118.8	10.7
1995	101.5	104.6	108.4	96.1	–5.5	87.8	98.1	128.2	10.2
1996	101.3	103.2	104.6	105.5	–3.7	95	99.1	123.6	9.9
1997	104.6	111.1	129.9	126.4	–2.1	104.9	100.1	118.3	8.7
1998	104.9	112.5	122.1	124.9	–4.8	103.6	101.4	114.3	7.8
1999	104.2	110.4	115.9	114.3	–5.1	102.5	103.2	110	7
2000	105.2	118.1	121.7	120.8	–8.6	101.5	101	109.8	6.4
2001	103.8	103.6	107.7	104	–6.2	106.4	100.3	109.2	5.7
2002	103.5	102.8	105.9	105.1	–7.1	113.6	100.1	105.3	5.8
2003	102.9	106.4	109.1	110.1	–8.9	109.2	101.3	104.7	5.9
2004	104.6	107.4	118.4	115.2	–8.7	98.9	99.4	106.8	6.1
2005	104.1	107	111.5	106.1	–7.5	106.3	100	103.6	7.2
2006	103.9	109.9	118	114.4	–7.4	103.5	100.7	103.9	7.5
2007	101.1	108.2	115.8	112	–7.3	95.4	99.9	108	7.4
2008	100.5	98.9	104.2	104.3	–7.3	100.8	98.8	106.1	7.8

* Previous year = 100

Source: The Hungarian Labour Market – Review and Analysis 2009, eds: Károly Fazekas, Anna Lovász, Álmos Telegdy, p 227., The Hungarian Labour Market – Review and Analysis 2005, eds: Károly Fazekas, Júlia Varga, p 150.

Table 2.2: Means (standard deviations) of firm-level variables, Hungarian WES, 1986-2008

Period	Value added (deflated, thousand HUF)	Capital (deflated, thousand HUF)	Employment	Observations (firm-years)
1986-1989	10887.88 (45213.07)	5489.43 (33876.01)	681.96 (2580.39)	7,620
1992-1995	3545.46 (19576.20)	3661.64 (37398.86)	334.36 (1733.96)	14,771
1996-2000	3375.49 (20093.9)	2237.20 (23477.99)	229.07 (1203.45)	24,266
2001-2005	2929.44 (22009.32)	1742.35 (18648.03)	150.12 (905.32)	34,579
2006-2008	3417.289 (25261.18)	1797.35 (16651.6)	139.89 (687.13)	20,971

Table 2.3: Means (standard deviations) of firm-level worker shares, Hungarian WES, 1986-2008

Period	At least 45	Educated (college or high school)	Educated, below 45	Educated, at least 45	Not educated, below 45	Not educated, at least 45
1986-1989	0.311 (0.096)	0.285 (0.175)	0.224 (0.137)	0.062 (0.058)	0.465 (0.140)	0.250 (0.104)
1992-1995	0.327 (0.189)	0.373 (0.253)	0.243 (0.202)	0.131 (0.137)	0.431 (0.230)	0.196 (0.158)
1996-2000	0.356 (0.213)	0.396 (0.280)	0.244 (0.229)	0.152 (0.153)	0.400 (0.247)	0.204 (0.176)
2001-2005	0.391 (0.236)	0.477 (0.314)	0.294 (0.268)	0.182 (0.180)	0.315 (0.247)	0.209 (0.195)
2006-2008	0.389 (0.246)	0.502 (0.324)	0.323 (0.284)	0.179 (0.183)	0.288 (0.246)	0.210 (0.207)

Table 2.4: Means of firm-level variables, subsamples of foreign, domestic private, and state-owned firms

	Value added			Capital			Employment			Observations		
Period	***Foreign***	***Domestic***	***State***	***Foreign***	***Domestic***	***State***	***Foreign***	***Domestic***	***State***	***Foreign***	***Domestic***	***State***
1986-1989			10,887			5,489			682			7,620
1992-1995	6,823	1,630	7,335	4,183	966	11,182	387	177	761	1,672	9,405	3,353
1996-2000	9,153	1,568	6,778	5,275	712	8,978	380	135	717	4,344	17,796	2,079
2001-2005	9,016	1,429	4,490	4,860	614	6,485	309	84	490	5,952	26,213	2,341
2006-2008	10,585	1,651	3,046	4,321	856	5,000	303	80	329	3,865	15,547	1,525

Table 2.5: Means of firm-level worker shares, subsamples of foreign, domestic private, and state-owned firms

	At least 45			Educated			Educated, at least 45			Educated, below 45		
Period	***Foreign***	***Domestic***	***State***	***Foreign***	***Domestic***	***State***	***Foreign***	***Domestic***	***State***	***Foreign***	***Domestic***	***State***
1986-1989			0.31			0.29			0.06			0.22
1992-1995	0.27	0.33	0.35	0.46	0.35	0.40	0.13	0.12	0.15	0.33	0.22	0.25
1996-2000	0.28	0.37	0.42	0.48	0.37	0.41	0.13	0.15	0.19	0.34	0.22	0.22
2001-2005	0.31	0.40	0.52	0.54	0.46	0.47	0.15	0.18	0.24	0.39	0.28	0.23
2006-2008	0.30	0.40	0.53	0.57	0.48	0.50	0.15	0.18	0.25	0.43	0.30	0.25

Table 2.6: Production function estimates, restricted model

	1986, 1989	1992-1995	1996-2000	2001-2005	2006-2008
OLS					
skilled / unskilled	0.920 *0.0956****	1.103 *0.0467****	1.286 *0.0392****	1.157 *0.0293****	1.126 *0.0357****
old / young	-0.264 *0.104***	-0.327 *0.0477****	-0.404 *0.0405****	-0.233 *0.0333****	-0.254 *0.0430****
LP					
skilled / unskilled	0.632 *0.0924****	0.919 *0.0463****	1.149 *0.0381****	0.945 *0.0285****	0.912 *0.0345****
old / young	-0.220 *0.0955***	-0.253 *0.0448****	-0.372 *0.0385****	-0.174 *0.0317****	-0.195 *0.0407****
FE					
skilled / unskilled	-0.0691 *0.0885*	0.0585 *0.0519*	0.0339 *0.0336*	0.0658 *0.0279***	0.0443 *0.0295*
old / young	-0.0989 *0.0819*	-0.0962 *0.0448***	-0.0677 *0.0316***	-0.0539 *0.0305**	-0.0370 *0.0463*
FE+LP					
skilled / unskilled	-0.0735 *0.0833*	0.0466 *0.0509*	0.0242 *0.0324*	0.0679 *0.0277***	0.0427 *0.0290*
old / young	-0.113 *0.0812*	-0.0947 *0.0440***	-0.0462 *0.0309*	-0.0533 *0.0304**	-0.0337 *0.0464*
Obs	7,591	14,264	23,934	33,616	19,828

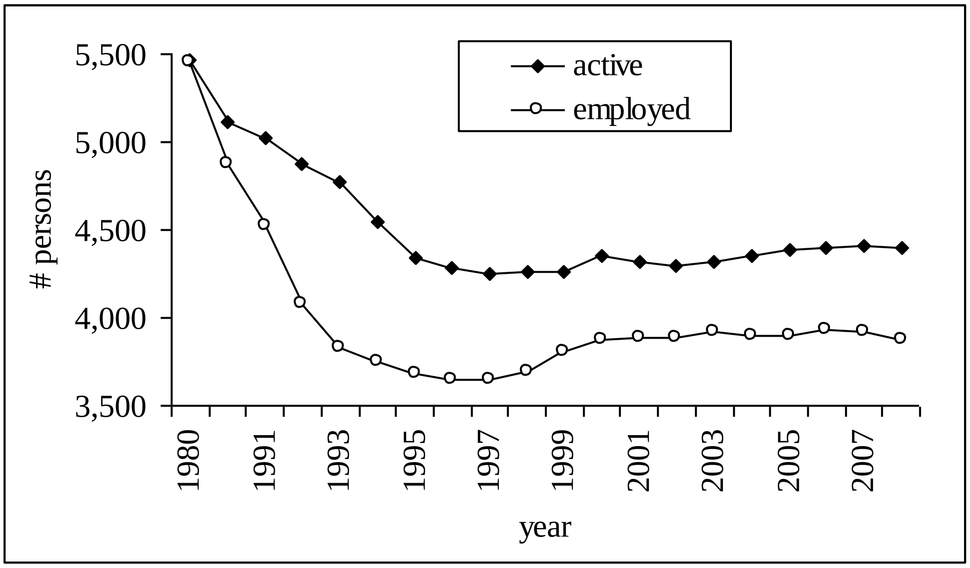
Standard errors in Italic, stars indicate significance levels: *p<0.1, **p<0.05, ***p<0.01. Standard errors are robust to firm-level clustering. The four panels reflect the estimation methods: least squares (OLS), firm fixed effects (FE), Levinsohn and Petrin method (LP), and its combination with firm fixed effects (FE+LP). Coefficient estimates are only presented for the worker share variables.

Table 2.7: Production function estimates, partially unrestricted model

	OLS					LP + FE				
	1986, 1989	**1992-1995**	**1996-2000**	**2001-2005**	**2006-2008**	**1986, 1989**	**1992-1995**	**1996-2000**	**2001-2005**	**2006-2008**
ALL FIRMS										
skilled old / skilled young	0.283	-0.483	-0.645	-0.190	-0.291	0.0728	-0.0990	-0.132	-0.104	-0.0480
	0.290	*0.0916****	*0.0762****	*0.0534****	*0.0701****	*0.222*	*0.0815*	*0.0546***	*0.0445***	*0.0606*
unskilled old / unskilled young	-0.398	-0.229	-0.234	-0.276	-0.217	-0.175	-0.0925	-0.0037	-0.0235	-0.0231
	*0.110****	*0.0574****	*0.0488****	*0.0443****	*0.0556****	*0.0776***	*0.0499**	*0.0345*	*0.0357*	*0.0545*
Obs	7,591	14,264	23,934	33,616	19,828	7,591	14,264	23,934	33,616	19,828
FOREIGN FIRMS										
skilled old / skilled young	-1.916	-0.957	-0.792	-0.294	-0.268	0.888	-0.602	-0.0087	-0.176	0.0551
	2.599	*0.258****	*0.191****	*0.150**	*0.217*	*1.343*	*0.248***	*0.118*	*0.114*	*0.109*
unskilled old / unskilled young	-0.985	-0.262	-0.157	-0.159	0.00986	-0.103	-0.465	-0.0570	-0.0646	-0.126
	1.485	*0.219*	*0.130*	*0.114*	*0.146*	*0.750*	*0.151****	*0.0842*	*0.0870*	*0.163*
Obs	182	1,655	4,298	5,833	3,721	182	1,655	4,298	5,833	3,721
DOMESTIC FIRMS										
skilled old / skilled young	0.338	-0.437	-0.625	-0.210	-0.259	0.328	0.0237	-0.179	-0.101	-0.0121
	0.299	*0.104****	*0.0858****	*0.0577****	*0.0746****	*0.191**	*0.0925*	*0.0629****	*0.0499***	*0.0600*
unskilled old / unskilled young	-0.392	-0.221	-0.273	-0.356	-0.329	-0.0381	-0.0038	0.0110	0.000142	0.0230
	*0.115****	*0.0650****	*0.0547****	*0.0482****	*0.0611****	*0.0862*	*0.0569*	*0.0410*	*0.0412*	*0.0605*
Obs	3,255	9,306	17,589	25,715	14,821	3,255	9,306	17,589	25,715	14,821
STATE-OWNED FIRMS										
skilled old / skilled young	0.184	0.0462	-0.0092	0.902	-0.253	-0.0321	0.0591	-0.115	0.00775	-0.669
	0.409	*0.252*	*0.340*	*0.276****	*0.372*	*0.320*	*0.252*	*0.218*	*0.180*	*0.426*
unskilled old / unskilled young	-0.458	-0.115	-0.239	0.0801	0.359	-0.361	-0.202	0.0453	0.0283	-0.218
	*0.178***	*0.144*	*0.215*	*0.212*	*0.311*	*0.127****	*0.128*	*0.104*	*0.115*	*0.202*
Obs	4,210	1,937	1,499	1,888	1,277	4,210	1,937	1,499	1,888	1,277

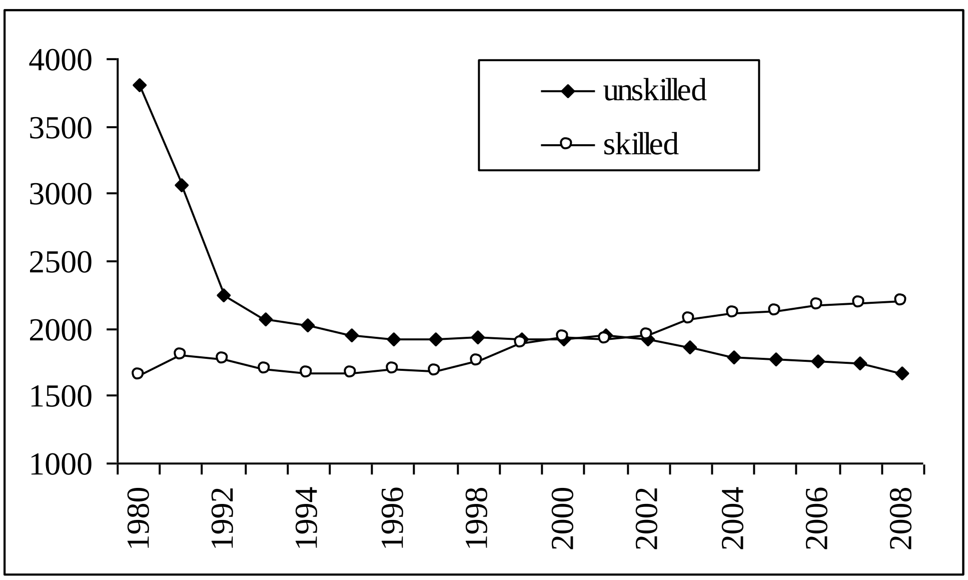
Standard errors in Italic, stars indicate significance levels: *p<0.1, **p<0.05, ***p<0.01. Standard errors are robust to firm-level clustering. Worker shares defined as: skilled = college or high school educated, young = aged below 45, old = aged at least 45. Coefficient estimates are only presented for the worker share variables of interest, the full result tables can be seen in Appendix Tables 2.8 – 2.11.

Figure 2.1: Number of active and employed persons in Hungary among the population aged over 15, thousands



Source: Central Statistical Office, stADAT

Figure 2.2: Number of employed by education among the population aged over 15, thousands



Source: Central Statistical Office, stADAT
Skilled stands for workers with high school or college education (at least 12 grades).

2.8 Appendix

APPENDIX: Full estimation results of the unrestricted specifications

Table 2.8: Unrestricted, *preferred specification*: no occupational shares, *all firms*, OLS and FE+LP

	OLS					LP + FE				
	1986, 1989	**1992-1995**	**1996-2000**	**2001-2005**	**2006-2008**	**1986, 1989**	**1992-1995**	**1996-2000**	**2001-2005**	**2006-2008**
ALL FIRMS										
lnK	0.318	0.130	0.220	0.233	0.222					
	*0.0182****	*0.00828****	*0.00746****	*0.00619****	*0.00724****					
lnL	0.637	0.857	0.807	0.822	0.844	0.209	0.542	0.520	0.542	0.547
	*0.0238****	*0.0136****	*0.0113****	*0.00989****	*0.0121****	*0.0292****	*0.0645****	*0.0276****	*0.0264****	*0.0396****
female share	0.438	-0.0500	-0.204	-0.242	-0.303	0.278	0.0195	0.00146	0.0871	0.0205
	*0.0939****	*0.0321*	*0.0391****	*0.0328****	*0.0397****	*0.0924****	*0.0212*	*0.0388*	*0.0375***	*0.0454*
skilled old share	0.283	-0.483	-0.645	-0.190	-0.291	0.0728	-0.0990	-0.132	-0.104	-0.0480
	0.290	*0.0916****	*0.0762****	*0.0534****	*0.0701****	*0.222*	*0.0815*	*0.0546***	*0.0445***	*0.0606*
unskilled young share	-0.747	-1.183	-1.419	-1.127	-1.152	0.141	-0.0487	-0.0687	-0.0959	-0.0518
	*0.122****	*0.0584****	*0.0484****	*0.0385****	*0.0465****	*0.102*	*0.0587*	*0.0370**	*0.0320****	*0.0342*
unskilled old share	-1.145	-1.412	-1.653	-1.403	-1.369	-0.0338	-0.141	-0.0724	-0.119	-0.0749
	*0.135****	*0.0685****	*0.0558****	*0.0451****	*0.0543****	*0.109*	*0.0683***	*0.0454*	*0.0407****	*0.0526*
Obs	7,591	14,264	23,934	33,616	19,828	7,591	14,264	23,934	33,616	19,828
R-squared	0.790	0.761	0.781	0.750	0.738	0.354	0.371	0.363	0.188	0.105

Standard errors in Italic, stars indicate significance levels: *p<0.1, **p<0.05, ***p<0.01. Standard errors are robust to firm-level clustering. Worker shares defined as: skilled = college or high school educated, unskilled = less than 12 grades completed, young = aged below 45, old = aged at least 45. Reference category: skilled young workers.

Table 2.9: Unrestricted, *preferred specification*: no occupational shares, majority *domestic firms*, OLS and FE+LP

	OLS					LP + FE				
	1986, 1989	**1992-1995**	**1996-2000**	**2001-2005**	**2006-2008**	**1986, 1989**	**1992-1995**	**1996-2000**	**2001-2005**	**2006-2008**
DOMESTIC										
lnK	0.342	0.126	0.212	0.231	0.225					
	*0.0249****	*0.00933****	*0.00838****	*0.00672****	*0.00765****					
lnL	0.647	0.859	0.828	0.836	0.870	0.204	0.632	0.539	0.527	0.547
	*0.0307****	*0.0158****	*0.0131****	*0.0110****	*0.0129****	*0.0278****	*0.0485****	*0.0318****	*0.0304****	*0.0462****
female share	0.239	-0.101	-0.220	-0.180	-0.210	0.229	0.00158	0.0600	0.0957	0.0232
	*0.127**	*0.0372****	*0.0453****	*0.0364****	*0.0437****	*0.132**	*0.0253*	*0.0470*	*0.0471***	*0.0540*
skilled old share	0.338	-0.437	-0.625	-0.210	-0.259	0.328	0.0237	-0.179	-0.101	-0.0121
	0.299	*0.104****	*0.0858****	*0.0577****	*0.0746****	*0.191**	*0.0925*	*0.0629****	*0.0499***	*0.0600*
unskilled young share	-0.694	-1.032	-1.299	-1.013	-0.994	0.127	-0.00996	-0.0708	-0.0900	-0.0379
	*0.145****	*0.0715****	*0.0562****	*0.0419****	*0.0501****	*0.111*	*0.0690*	*0.0439*	*0.0370***	*0.0405*
unskilled old share	-0.302	-1.253	-1.573	-1.370	-1.322	0.166	-0.0137	-0.0598	-0.0899	-0.0149
	*0.135***	*0.0819****	*0.0652****	*0.0486****	*0.0593****	*0.103*	*0.0846*	*0.0532*	*0.0471**	*0.0592*
Obs	3,255	9,306	17,589	25,715	14,821	3,255	9,306	17,589	25,715	14,821
R-squared	0.854	0.727	0.740	0.701	0.699	0.447	0.346	0.311	0.175	0.109

Standard errors in Italic, stars indicate significance levels: *p<0.1, **p<0.05, ***p<0.01. Standard errors are robust to firm-level clustering. Worker shares defined as: skilled = college or high school educated, unskilled = less than 12 grades completed, young = aged below 45, old = aged at least 45. Reference category: skilled young workers.

Table 2.10: Unrestricted, *preferred specification*: no occupational shares, majority *foreign firms*, OLS and FE+LP

	OLS					LP + FE				
	1986, 1989	**1992-1995**	**1996-2000**	**2001-2005**	**2006-2008**	**1986, 1989**	**1992-1995**	**1996-2000**	**2001-2005**	**2006-2008**
					FOREIGN					
lnK	0.462	0.262	0.274	0.235	0.209					
	*0.160****	*0.0314****	*0.0173****	*0.0149****	*0.0207****					
lnL	0.543	0.726	0.730	0.798	0.793	0.811	0.434	0.505	0.576	0.498
	*0.207****	*0.0423****	*0.0237****	*0.0227****	*0.0330****	*0.433**	*0.0926****	*0.0518****	*0.0532****	*0.0787****
female share	1.221	0.0808	-0.179	-0.326	-0.441	0.419	0.0343	-0.111	0.0954	0.0202
	0.906	*0.0927*	*0.0893***	*0.0825****	*0.0955****	*0.831*	*0.0580*	*0.0736*	*0.0679*	*0.0840*
skilled old share	-1.916	-0.957	-0.792	-0.294	-0.268	0.888	-0.602	-0.00867	-0.176	0.0551
	2.599	*0.258****	*0.191****	*0.150**	*0.217*	*1.343*	*0.248***	*0.118*	*0.114*	*0.109*
unskilled young share	-1.421	-1.703	-1.708	-1.652	-1.742	0.405	-0.0698	-0.0227	-0.126	-0.0680
	1.152	*0.156****	*0.104****	*0.101****	*0.120****	*0.630*	*0.141*	*0.0700*	*0.0667**	*0.0602*
unskilled old share	-0.436	-1.965	-1.864	-1.811	-1.732	0.508	-0.535	-0.0797	-0.190	-0.194
	0.989	*0.225****	*0.135****	*0.124****	*0.144****	*0.557*	*0.175****	*0.0930*	*0.0958***	*0.150*
Obs	182	1,655	4,298	5,833	3,721	182	1,655	4,298	5,833	3,721
R-squared	0.769	0.753	0.800	0.766	0.699	0.733	0.620	0.562	0.299	0.150

Standard errors in Italic, stars indicate significance levels: *p<0.1, **p<0.05, ***p<0.01. Standard errors are robust to firm-level clustering. Worker shares defined as: skilled = college or high school educated, unskilled = less than 12 grades completed, young = aged below 45, old = aged at least 45. Reference category: skilled young workers.

Table 2.11: Unrestricted, *preferred specification*: no occupational shares, *state-owned firms*, OLS and FE+LP

	OLS					**LP + FE**				
	1986, 1989	**1992-1995**	**1996-2000**	**2001-2005**	**2006-2008**	**1986, 1989**	**1992-1995**	**1996-2000**	**2001-2005**	**2006-2008**
STATE-OWNED										
lnK	0.315	0.0770	0.156	0.249	0.282					
	*0.0228****	*0.0214****	*0.0438****	*0.0379****	*0.0388****					
lnL	0.617	0.924	0.807	0.751	0.698	0.186	0.893	0.422	0.445	0.697
	*0.0308****	*0.0341****	*0.0560****	*0.0579****	*0.0692****	*0.0425****	*0.114****	*0.118****	*0.194***	*0.274***
female share	0.458	0.284	0.0611	-0.514	-0.617	0.264	0.182	0.0350	-0.0615	0.181
	*0.125****	*0.0882****	*0.172*	*0.209***	*0.245***	*0.131***	*0.0691****	*0.123*	*0.147*	*0.202*
skilled old share	0.184	0.0462	-0.00921	0.902	-0.253	-0.0321	0.0591	-0.115	0.00775	-0.669
	0.409	*0.252*	*0.340*	*0.276****	*0.372*	*0.320*	*0.252*	*0.218*	*0.180*	*0.426*
unskilled young share	-1.010	-0.897	-1.300	-0.628	-1.008	0.136	-0.0849	-0.102	-0.0964	-0.222
	*0.172****	*0.164****	*0.232****	*0.248***	*0.340****	*0.147*	*0.135*	*0.163*	*0.178*	*0.178*
unskilled old share	-1.468	-1.012	-1.538	-0.547	-0.650	-0.225	-0.287	-0.0562	-0.0682	-0.440
	*0.196****	*0.173****	*0.251****	*0.262***	*0.296***	*0.169*	*0.153**	*0.180*	*0.174*	*0.240**
Obs	4,210	1,937	1,499	1,888	1,277	4,210	1,937	1,499	1,888	1,277
R-squared	0.765	0.769	0.794	0.786	0.740	0.323	0.532	0.497	0.217	0.180

Standard errors in Italic, stars indicate significance levels: *p<0.1, **p<0.05, ***p<0.01. Standard errors are robust to firm-level clustering. Worker shares defined as: skilled = college or high school educated, unskilled = less than 12 grades completed, young = aged below 45, old = aged at least 45. Reference category: skilled young workers.

Table 2.12: Unrestricted, with educated defined as *college* only, no occupational shares, *all firms*, OLS and FE+LP

	OLS					LP + FE				
	1986, 1989	**1992-1995**	**1996-2000**	**2001-2005**	**2006-2008**	**1986, 1989**	**1992-1995**	**1996-2000**	**2001-2005**	**2006-2008**
ALL FIRMS										
lnK	0.324	0.144	0.235	0.242	0.228					
	*0.0180****	*0.00837****	*0.00743****	*0.00613****	*0.00711****					
lnL	0.626	0.836	0.776	0.795	0.821	0.214	0.541	0.522	0.542	0.544
	*0.0233****	*0.0136****	*0.0114****	*0.00976****	*0.0118****	*0.0284****	*0.0645****	*0.0275****	*0.0263****	*0.0396****
female share	0.551	0.0327	-0.0520	-0.0968	-0.144	0.229	0.0211	0.00882	0.0967	0.0301
	*0.0917****	*0.0331*	*0.0398*	*0.0331****	*0.0399****	*0.0827****	*0.0213*	*0.0389*	*0.0378***	*0.0451*
skilled old share	-0.454	-1.005	-0.887	-0.458	-0.421	0.603	-0.144	-0.220	-0.114	0.0287
	0.823	*0.179****	*0.157****	*0.107****	*0.152****	*0.646*	*0.175*	*0.114**	*0.0938*	*0.122*
unskilled young share	-2.180	-1.906	-2.115	-1.722	-1.649	0.123	-0.116	-0.209	-0.198	0.00941
	*0.305****	*0.112****	*0.0901****	*0.0656****	*0.0735****	*0.299*	*0.170*	*0.0765****	*0.0632****	*0.0560*
unskilled old share	-2.567	-2.149	-2.446	-2.000	-1.948	-0.0173	-0.205	-0.238	-0.245	-0.0337
	*0.312****	*0.116****	*0.0920****	*0.0676****	*0.0768****	*0.300*	*0.167*	*0.0796****	*0.0684****	*0.0706*
Obs	7,591	14,264	23,934	33,616	19,828	7,591	14,264	23,934	33,616	19,828
R-squared	0.791	0.756	0.779	0.748	0.739	0.355	0.371	0.363	0.189	0.105

Standard errors in Italic, stars indicate significance levels: *p<0.1, **p<0.05, ***p<0.01. Standard errors are robust to firm-level clustering. Worker shares defined as: skilled = college or high school educated, unskilled = less than 12 grades completed, young = aged below 45, old = aged at least 45. Reference category: skilled young workers.

Table 2.13: Unrestricted, with educated defined as *college* only, no occupational shares, majority *domestic firms*, OLS and FE+LP

	OLS					LP + FE				
	1986, 1989	**1992-1995**	**1996-2000**	**2001-2005**	**2006-2008**	**1986, 1989**	**1992-1995**	**1996-2000**	**2001-2005**	**2006-2008**
DOMESTIC										
lnK	0.355	0.137	0.224	0.237	0.228					
	*0.0249****	*0.00926****	*0.00830****	*0.00670****	*0.00763****					
lnL	0.625	0.839	0.797	0.807	0.844	0.208	0.632	0.544	0.527	0.545
	*0.0303****	*0.0157****	*0.0131****	*0.0109****	*0.0128****	*0.0268****	*0.0484****	*0.0318****	*0.0304****	*0.0462****
female share	0.328	-0.0256	-0.0840	-0.0431	-0.0726	0.204	0.00372	0.0654	0.104	0.0312
	*0.125****	*0.0382*	*0.0458**	*0.0369*	*0.0442*	*0.131*	*0.0253*	*0.0470*	*0.0474***	*0.0535*
skilled old share	0.263	-0.957	-1.126	-0.472	-0.477	0.450	-0.143	-0.333	-0.106	0.0273
	0.846	*0.220****	*0.179****	*0.120****	*0.167****	*0.600*	*0.235*	*0.143***	*0.113*	*0.127*
unskilled young share	-0.302	-1.803	-2.249	-1.615	-1.562	0.304	-0.199	-0.306	-0.175	0.0893
	0.360	*0.149****	*0.108****	*0.0788****	*0.0881****	*0.393*	*0.197*	*0.105****	*0.0869***	*0.0740*
unskilled old share	-0.657	-2.025	-2.592	-1.961	-1.916	0.323	-0.186	-0.333	-0.206	0.0965
	*0.357**	*0.152****	*0.111****	*0.0793****	*0.0912****	*0.371*	*0.199*	*0.107****	*0.0908***	*0.0843*
Obs	3,255	9,306	17,589	25,715	14,821	3,255	9,306	17,589	25,715	14,821
R-squared	0.852	0.723	0.738	0.698	0.698	1,782	0.346	0.312	0.175	0.109

Standard errors in Italic, stars indicate significance levels: *p<0.1, **p<0.05, ***p<0.01. Standard errors are robust to firm-level clustering. Worker shares defined as: skilled = college or high school educated, unskilled = less than 12 grades completed, young = aged below 45, old = aged at least 45. Reference category: skilled young workers.

Table 2.14: Unrestricted, with educated defined as *college* only, no occupational shares, majority *foreign firms*, OLS and FE+LP

	OLS					**LP + FE**				
	1986, 1989	**1992-1995**	**1996-2000**	**2001-2005**	**2006-2008**	**1986, 1989**	**1992-1995**	**1996-2000**	**2001-2005**	**2006-2008**
	FOREIGN									
lnK	0.473	0.292	0.288	0.249	0.223					
	*0.163****	*0.0324****	*0.0170****	*0.0141****	*0.0205****					
lnL	0.522	0.678	0.714	0.776	0.776	0.749	0.426	0.504	0.585	0.494
	*0.208***	*0.0441****	*0.0241****	*0.0217****	*0.0318****	*0.420**	*0.0910****	*0.0516****	*0.0525****	*0.0800****
female share	1.243	0.0421	-0.114	-0.204	-0.241	-0.0575	0.0321	-0.106	0.103	0.0328
	0.897	*0.0979*	*0.0917*	*0.0807***	*0.0945***	*0.704*	*0.0572*	*0.0738*	*0.0684*	*0.0831*
skilled old share	-1.043	-1.532	-0.326	-0.110	0.176	-4.218	-0.536	0.0131	-0.0468	0.0560
	6.783	*0.450****	*0.336*	*0.262*	*0.442*	*3.956*	*0.439*	*0.199*	*0.188*	*0.205*
unskilled young share	0.165	-1.767	-1.830	-1.919	-1.805	-2.599	0.133	-0.0379	-0.234	-0.0746
	2.448	*0.221****	*0.155****	*0.129****	*0.143****	*1.353**	*0.310*	*0.103*	*0.0858****	*0.0772*
unskilled old share	-1.132	-2.169	-2.256	-2.202	-2.049	-1.239	-0.388	-0.0812	-0.346	-0.148
	2.204	*0.273****	*0.165****	*0.143****	*0.160****	*1.104*	*0.375*	*0.121*	*0.111****	*0.147*
Obs	182	1,655	4,298	5,833	3,721	182	1,655	4,298	5,833	3,721
R-squared	0.768	0.735	0.796	0.771	0.704	101	0.620	0.562	0.301	0.148

Standard errors in Italic, stars indicate significance levels: *p<0.1, **p<0.05, ***p<0.01. Standard errors are robust to firm-level clustering. Worker shares defined as: skilled = college or high school educated, unskilled = less than 12 grades completed, young = aged below 45, old = aged at least 45. Reference category: skilled young workers.

Table 2.15: Unrestricted, with educated defined as *college* only, no occupational shares, *state-owned firms*, OLS and FE+LP

	OLS					LP + FE				
	1986, 1989	**1992-1995**	**1996-2000**	**2001-2005**	**2006-2008**	**1986, 1989**	**1992-1995**	**1996-2000**	**2001-2005**	**2006-2008**
STATE-OWNED										
lnK	0.322	0.0830	0.175	0.259	0.291					
	*0.0224****	*0.0212****	*0.0438****	*0.0370****	*0.0372****					
lnL	0.608	0.915	0.773	0.746	0.688	0.187	0.880	0.427	0.443	0.762
	*0.0301****	*0.0333****	*0.0560****	*0.0576****	*0.0672****	*0.0416****	*0.113****	*0.118****	*0.194***	*0.292****
female share	0.616	0.416	0.478	-0.258	-0.409	0.217	0.196	0.0648	-0.0497	0.201
	*0.123****	*0.0885****	*0.165****	*0.201*	*0.223**	*0.109***	*0.0701****	*0.136*	*0.148*	*0.196*
skilled old share	-0.784	0.0417	-1.247	0.401	-0.0325	0.946	0.0801	-0.606	-0.130	0.260
	1.049	*0.566*	*0.813*	*0.651*	*0.719*	*0.902*	*0.508*	*0.553*	*0.621*	*0.793*
unskilled young share	-2.727	-1.446	-2.373	-1.020	-0.674	0.193	-0.486	-0.377	0.0334	-0.318
	*0.378****	*0.380****	*0.490****	*0.492***	*0.475*	*0.360*	*0.465*	*0.436*	*0.387*	*0.386*
unskilled old share	-3.215	-1.563	-2.471	-0.611	-0.613	-0.145	-0.618	-0.332	0.0568	-0.780
	*0.392****	*0.373****	*0.517****	*0.469*	*0.439*	*0.376*	*0.443*	*0.429*	*0.396*	*0.543*
Obs	4,210	1,937	1,499	1,888	1,277	4,210	1,937	1,499	1,888	1,277
R-squared	0.767	0.767	0.784	0.777	0.737	0.325	0.534	0.498	0.217	0.186

Standard errors in Italic, stars indicate significance levels: *p<0.1, **p<0.05, ***p<0.01. Standard errors are robust to firm-level clustering. Worker shares defined as: skilled = college or high school educated, unskilled = less than 12 grades completed, young = aged below 45, old = aged at least 45. Reference category: skilled young workers.

Table 2.16: Unrestricted, including occupational shares, *all firms*, OLS and FE+LP

	OLS					**LP + FE**				
	1986, 1989	**1992-1995**	**1996-2000**	**2001-2005**	**2006-2008**	**1986, 1989**	**1992-1995**	**1996-2000**	**2001-2005**	**2006-2008**
ALL FIRMS										
lnK	0.297	0.129	0.212	0.223	0.214					
	*0.0180****	*0.00825****	*0.00728****	*0.00603****	*0.00708****					
lnL	0.643	0.857	0.824	0.843	0.861	0.213	0.546	0.522	0.553	0.545
	*0.0242****	*0.0136****	*0.0111****	*0.00971****	*0.0118****	*0.0295****	*0.0647****	*0.0276****	*0.0266****	*0.0395****
female share	-0.159	-0.120	-0.385	-0.450	-0.458	0.275	0.0112	-0.0117	0.0687	0.0453
	*0.0923**	*0.0325****	*0.0407****	*0.0334****	*0.0416****	*0.0969****	*0.0209*	*0.0398*	*0.0396**	*0.0483*
skilled old share	-0.115	-0.555	-0.731	-0.293	-0.318	0.0841	-0.105	-0.140	-0.116	-0.0551
	0.280	*0.0916****	*0.0738****	*0.0527****	*0.0672****	*0.221*	*0.0824*	*0.0545****	*0.0453***	*0.0623*
unskilled young share	-0.238	-0.742	-0.661	-0.381	-0.400	0.160	-0.00758	-0.0250	-0.0501	-0.0604
	*0.144**	*0.0683****	*0.0571****	*0.0420****	*0.0517****	*0.137*	*0.0593*	*0.0367*	*0.0313*	*0.0353**
unskilled old share	-0.520	-0.975	-0.910	-0.632	-0.611	-0.0113	-0.0934	-0.0235	-0.0689	-0.0871
	*0.153****	*0.0754****	*0.0630****	*0.0474****	*0.0569****	*0.149*	*0.0690*	*0.0459*	*0.0398**	*0.0528**
Obs	7,591	14,264	23,934	33,616	19,828	7,591	14,264	23,934	33,616	19,828
R-squared	0.805	0.765	0.791	0.763	0.751	0.356	0.372	0.364	0.189	0.106

Standard errors in Italic, stars indicate significance levels: *p<0.1, **p<0.05, ***p<0.01. Standard errors are robust to firm-level clustering. Worker shares defined as: skilled = college or high school educated, unskilled = less than 12 grades completed, young = aged below 45, old = aged at least 45. Reference category: skilled young workers.

Table 2.17: Unrestricted, including occupational shares, majority *domestic firms*, OLS and FE+LP

	OLS					LP + FE				
	1986, 1989	**1992-1995**	**1996-2000**	**2001-2005**	**2006-2008**	**1986, 1989**	**1992-1995**	**1996-2000**	**2001-2005**	**2006-2008**
	DOMESTIC									
lnK	0.331	0.123	0.204	0.220	0.215					
	*0.0237****	*0.00933****	*0.00823****	*0.00658****	*0.00753****					
lnL	0.653	0.857	0.843	0.857	0.889	0.204	0.644	0.541	0.535	0.545
	*0.0285****	*0.0158****	*0.0128****	*0.0108****	*0.0127****	*0.0272****	*0.0479****	*0.0318****	*0.0307****	*0.0458****
female share	-0.184	-0.160	-0.416	-0.436	-0.413	0.210	-0.0101	0.0369	0.0849	0.0576
	*0.109**	*0.0380****	*0.0485****	*0.0383****	*0.0467****	*0.136*	*0.0250*	*0.0475*	*0.0498**	*0.0578*
skilled old share	0.114	-0.516	-0.752	-0.323	-0.302	0.321	-0.00325	-0.201	-0.113	-0.00826
	0.277	*0.104****	*0.0830****	*0.0571****	*0.0726****	*0.185**	*0.0934*	*0.0629****	*0.0506***	*0.0619*
unskilled young share	-0.0564	-0.607	-0.691	-0.387	-0.386	0.173	0.0374	-0.0163	-0.0658	-0.0561
	0.176	*0.0792****	*0.0650****	*0.0452****	*0.0553****	*0.131*	*0.0766*	*0.0434*	*0.0360**	*0.0420*
unskilled old share	-0.256	-0.835	-0.954	-0.691	-0.673	0.151	0.0313	-0.00312	-0.0593	-0.0365
	0.187	*0.0885****	*0.0723****	*0.0512****	*0.0619****	*0.142*	*0.0889*	*0.0537*	*0.0461*	*0.0596*
Obs	3,255	9,306	17,589	25,715	14,821	3,255	9,306	17,589	25,715	14,821
R-squared	0.867	0.731	0.750	0.716	0.712	0.448	0.348	0.313	0.175	0.110

Standard errors in Italic, stars indicate significance levels: *p<0.1, **p<0.05, ***p<0.01. Standard errors are robust to firm-level clustering. Worker shares defined as: skilled = college or high school educated, unskilled = less than 12 grades completed, young = aged below 45, old = aged at least 45. Reference category: skilled young workers.

Table 2.18: Unrestricted, including occupational shares, majority *foreign firms*, OLS and FE+LP

	OLS					LP + FE				
	1986, 1989	**1992-1995**	**1996-2000**	**2001-2005**	**2006-2008**	**1986, 1989**	**1992-1995**	**1996-2000**	**2001-2005**	**2006-2008**
					FOREIGN					
lnK	0.577	0.265	0.266	0.229	0.208					
	*0.183****	*0.0314****	*0.0170****	*0.0144****	*0.0199****					
lnL	0.297	0.720	0.759	0.826	0.810	1.063	0.437	0.500	0.596	0.497
	0.227	*0.0424****	*0.0232****	*0.0218****	*0.0305****	*0.329****	*0.0907****	*0.0519****	*0.0517****	*0.0804****
female share	0.449	0.0185	-0.269	-0.309	-0.360	0.00350	0.0285	-0.0810	0.0778	0.0417
	0.838	*0.0906*	*0.0842****	*0.0746****	*0.0918****	*0.897*	*0.0591*	*0.0760*	*0.0696*	*0.0912*
skilled old share	-1.516	-0.967	-0.722	-0.324	-0.123	2.450	-0.590	-0.00411	-0.178	0.0602
	2.291	*0.260****	*0.179****	*0.145***	*0.195*	*1.099***	*0.253***	*0.117*	*0.116*	*0.110*
unskilled young share	-0.0888	-1.234	-0.524	-0.452	-0.512	1.577	-0.0554	-0.0664	0.0209	-0.0675
	1.370	*0.225****	*0.120****	*0.117****	*0.144****	*1.083*	*0.139*	*0.0718*	*0.0638*	*0.0652*
unskilled old share	-1.492	-1.530	-0.779	-0.694	-0.629	1.613	-0.531	-0.121	-0.0479	-0.199
	1.424	*0.260****	*0.150****	*0.134****	*0.157****	*1.166*	*0.170****	*0.0974*	*0.0852*	*0.147*
Obs	182	1,655	4,298	5,833	3,721	182	1,655	4,298	5,833	3,721
R-squared	0.815	0.758	0.817	0.787	0.722	0.808	0.621	0.563	0.303	0.151

Standard errors in Italic, stars indicate significance levels: *p<0.1, **p<0.05, ***p<0.01. Standard errors are robust to firm-level clustering. Worker shares defined as: skilled = college or high school educated, unskilled = less than 12 grades completed, young = aged below 45, old = aged at least 45. Reference category: skilled young workers.

Table 2.19: Unrestricted, including occupational shares, *state-owned firms*, OLS and FE+LP

	OLS					LP + FE				
	1986, 1989	**1992-1995**	**1996-2000**	**2001-2005**	**2006-2008**	**1986, 1989**	**1992-1995**	**1996-2000**	**2001-2005**	**2006-2008**
STATE-OWNED										
lnK	0.285	0.0711	0.138	0.231	0.261					
	*0.0229****	*0.0211****	*0.0398****	*0.0355****	*0.0370****					
lnL	0.631	0.941	0.841	0.790	0.737	0.192	0.877	0.420	0.454	0.763
	*0.0319****	*0.0339****	*0.0524****	*0.0548****	*0.0661****	*0.0437****	*0.109****	*0.115****	*0.197***	*0.276****
female share	-0.215	0.162	-0.261	-0.901	-0.733	0.272	0.183	0.0713	0.00415	-0.0214
	0.135	*0.0964**	*0.196*	*0.213****	*0.273****	*0.138***	*0.0716***	*0.138*	*0.182*	*0.241*
skilled old share	-0.199	0.00905	-0.277	0.858	-0.239	-0.0221	0.110	-0.0734	-0.0469	-0.877
	0.396	*0.258*	*0.291*	*0.247****	*0.347*	*0.317*	*0.271*	*0.221*	*0.220*	*0.449**
unskilled young share	-0.330	-0.467	-0.410	0.260	-0.0243	0.183	-0.100	-0.104	-0.118	-0.108
	0.204	*0.168****	*0.247**	*0.265*	*0.364*	*0.222*	*0.152*	*0.136*	*0.219*	*0.234*
unskilled old share	-0.769	-0.551	-0.669	0.416	0.301	-0.182	-0.289	-0.0360	-0.120	-0.288
	*0.221****	*0.183****	*0.276***	*0.264*	*0.336*	*0.246*	*0.175**	*0.162*	*0.228*	*0.261*
Obs	4,210	1,937	1,499	1,888	1,277	4,210	1,937	1,499	1,888	1,277
R-squared	0.782	0.773	0.805	0.799	0.753	0.326	0.532	0.502	0.217	0.195

Standard errors in Italic, stars indicate significance levels: *p<0.1, **p<0.05, ***p<0.01. Standard errors are robust to firm-level clustering. Worker shares defined as: skilled = college or high school educated, unskilled = less than 12 grades completed, young = aged below 45, old = aged at least 45. Reference category: skilled young workers.

CHAPTER 3

3 Productivity and Age: Evidence from Hungarian Firm-Level Data

3.1 Introduction

The rapid advance of science substantially improved the living and working conditions of people and opened up the possibility of a longer life horizon for the individuals. However, the individual advantages are coupled with increasing societal burdens. An ageing population – being the consequence of longer life expectancy and lower birth rates – increases the burden on the health care and on the pension systems. Increasing old age dependency ratio – the number of people over 65 relative to the working age (15-65 years old) population – is a good indicator of the above trends. According to Eurostat figures, in 2005 the old age dependency ratio was 24.7 percent in the EU27 countries, and it is expected to more than double by 2060.

A potential policy tool to alleviate the increasing fiscal burdens of an ageing society is to lengthen the active working years of the employees. The EU has set the objective of raising the employment of people aged 55-64 to a rate of 50 percent by 2010. Though employment increased in the EU between 2000 and 2008, and reached an average of 45 percent for the older age group by 2010, there are countries, which substantially lag behind in improving the employability of older employees. One of the reasons for the reluctance of firms to employ older people may be the "assumed" lower productivity of this worker group. Thus, from the firms' point of view, the issue of increasing the employability of older employees is strongly connected to how older workers contribute to the production, and more generally, how the productivity of workers changes through the life-cycle. The current paper addresses this issue by comparing the productivity of the older worker group to the productivity of younger employees. The methodology draws on the work of Hellerstein and Neumark (1999) estimating the firm-level relative productivity of various worker groups. To carry out the exercise, a linked employer-employee dataset is used, and a production function augmented with the age composition of the workforce is estimated.

The research question is particularly relevant in Hungary, where both the demographic trends and the low employment rate of the older worker groups make it difficult to cope with the increasing economic burdens of an ageing society. According to Eurostat, the old age dependency ratio was 22.7 percent in 2005, which was below the average value of 24.7 percent reported for EU27 countries. However, by 2060, the Hungarian number is forecasted to reach 57.8 percent, which is well above the projected figure for EU27 as a whole, and places Hungary among countries having the oldest population[83].

Besides the demographic developments, unfavorable employment trends pose another large challenge. In Hungary the employment rate, especially for the older worker group, strongly lags behind other EU countries. In 2005, only one-third of the 55 – 64 age group was employed, which was much below the average 40.5 percent value of the EU-25 countries (Adler et al, 2005). Roughly 10 percent of those between the ages of 20 and 60 belong already to the group of retired people, and the majority of older employees leaves the labor force before reaching the retirement age (Hablicsek 2004). Despite the various governmental reforms of the pension system, which raised the retirement age uniformly to 62 years to be

[83] Note, however, that in Hungary low fertility rate and the declining population are the major reasons of the ageing population (Hablicsek 2004). Though life expectancy increased substantially during the last century, it is currently shorter than in many other EU countries. According to Eurostat, life expectancy at birth for the EU27 countries was 76.4 years for males and 82.4 for females in 2008. The similar numbers for Hungary were 70 and 78.3, respectively.

reached by 2014, it is possible to retire already at the age of 56 (Szeman et al 2007)[84]. The frequent use of early retirement options and disability benefits suggest that Hungarian employees have high willingness to retire early. On the other hand, survey studies and interviews suggest that employers' attitude is not favorable towards older employees. Using the International Survey Program data from 1997, Dorn and Sousa-Poza (2010) reports that in Hungary the ratio of early retirees among the 45-69 age group is 34 percent, and 62 percent of the early retirements is involuntary. Among the 19 countries covered by their study, Hungary is ranked as the first one regarding the percentage of involuntary early retirement. Another study analyzing 3000 job advertisements found that 8 percent specified the age, and in most cases young persons were considered to be no older than 40 (Szeman et al 2007). An empirical study by Adler et al (2005) covering 500 firms and 1.3 million employees found that in spite of the formal policy measures to increase the employment rate of older employees, there are signs of strong discrimination against this worker group[85]. Thus, in Hungary, both the demographic trends, the low employment rate of the older worker group and the often discriminative attitudes of the employers urge to analyze the question of how the employability of the older worker group could be promoted. From the firms' point of view, a crucial element of the problem relates to how the productivity of employees changes as they grow older.

Skirbekk (2004) gives a concise summary of the findings on the relationship between age and productivity. Accordingly, empirical results focusing on the various determinants of

[84] The governmental reform of the pension system introduced several early retirement options: advanced pension, reduced advanced pension with penalty for shorter service period. For example, in 2007 the retirement age was 61 years, but using the advanced retirement option it was possible to retire at the age of 56 having 38 years of services (Szeman et al 2007).

[85] The study found that employers are reluctant to hire workers above 45 into new jobs. During the last three years before the study, 31 percent of the new hires were from the above 45 age group, while their share within the firms, on average, was 45 percent. Turning to the firing practices of the firms, the study found that employees in the 45 – 55 age group are more often laid off than workers aged 15 – 29.

the productivity, such as physical, mental, cognitive abilities, experience and education, suggest that cognitive abilities decline from a certain age, but verbal abilities are quite stable over the life cycle. Experience increases productivity, but only up to a given duration, when the decline in cognitive abilities dominates. Besides, older employees are found to have difficulties with adapting to new working strategies.

Firm-level studies analyzing the various age groups' contribution to firm's output show mixed results. The conventional hump-shaped productivity-age profile is found by most cross-sectional studies, e.g. by Hellerstein and Neumark (2004) or Lallemand and Rycx (2009). On the other hand, panel estimates yield diverging results. While Vandenberghe, Waltenberg and Rigo (2012) documents an inverted U-shape age-productivity profile with the age group over 50 being the least productive, the estimates by Aubert and Crepon (2006), Göbel and Zwick (2009) and Ours and Stoeldraijer (2011) do not imply decreasing productivity with age. The differences between the diverging results may be partly due to differences in the estimation method and in the quality of the database, but my also reflect differences in the countries' labor market institutions, union activity, availability of training programs, etc. Additionally, the Hungarian experience may differ from those found in Western European countries due to the regime change in 1990, which brought about an environment with new technological and work practices, where employees had to adapt quickly to the new situation. The change hit severely the older worker group experiencing a strong devaluation of their labor-market skills.

In the paper I estimate the age-productivity profile of the firms using a large linked employer employee dataset from Hungary covering the years of 1992-2008. The database is representative of firms and employees, and includes accounting information on firm performance and several employee characteristics (gender, age, education, occupation). I group workers into detailed age categories, and control for the gender and educational composition of the workforce. As the database follows firms over time, I am able to take into account unobservable time invariant firm fixed effects. I apply numerous methodological techniques to address the issues of firm-level unobserved heterogeneity, and the simultaneity between the input and output decisions. The cross-sectional estimates will be provided by OLS and structural estimators (Levinsohn and Petrin 2003, Ackerberg, Caves and Frazer 2006). Within-estimates are obtained by demeaning (FE), first-differencing (FD) and long-differencing (LD). The final set of estimates takes into account both the heterogeneity and simultaneity issues, and use IV methods and structural approaches combined with demeaning of the data to eliminate firm fixed effects.

Thus, the paper contributes to the literature in several ways. First, it adds to the empirical literature on the relationship between the age composition of the firm and its productivity by using a large representative linked employer employee panel dataset from Hungary. Hungary is a country where the societal consequences of an aging population may be especially relevant due to the unfavorable demographic and employment trends. Besides, Hungary is a transitional country, where the productivity-age profile may differ from those documented in Western countries due to the sudden technological and organizational changes after the regime change. As empirical evidence on the age-productivity profiles of firms in Hungary is rather limited, this paper aims to fill in this gap[86]. Second, I assess the robustness of the estimates using several specifications and estimation methods. Due to the high quality of the database, I am able to group workers into detailed age categories, and control for several

[86] Chapter 2 of the current thesis focusing on the long-term impacts of skill obsolescence estimates the relative productivity of the over 45/below 45 age groups. Kertesi and Köllő (2002), using a shorter database and yearly OLS regression, also estimates production function including the share of more and less experienced workers as controls. Besides the above two papers, there are no studies analyzing the age-productivity profiles of firms in Hungary.

employee and employer characteristics[87]. Both the problems of unobserved heterogeneity and simultaneity between the input and output decisions will be analyzed, and estimates will be compared over a wide range of methods. Particularly, estimates using the structural approach by Ackerberg, Caves and Frazer (2006) are rather limited, and include only few studies in the worker composition – productivity literature[88].

The results using the 1992-2008 panel of firms document a decreasing age – productivity profile with a significant drop of productivity at the ages of 35, 45 and 55. However, splitting the panel into two samples (before and after 2000) reveals that the productivity disadvantage of older employees disappears in the second period. Therefore, the Hungarian results covering the most recent year do not confirm the skepticism over the negative impact of the aging population on firms' productivity.

The paper is organized as follows. Section 3.2 gives an overview of the methodology and the estimation methods. Results from previous studies are summarized in Section 3.3. Section 3.4 describes the data and provides some descriptive statistics. Baseline results are presented in Section 3.5.1, and some robustness checks experimenting with more detailed worker categories, period and industry subsamples are discussed in Section 3.5.2. Finally, Section 3.6. concludes.

[87] There are many datasets missing crucial control variables. For example, Dostie (2001) and Ours and Stoeldraijer (2011) do not have a capital variable. Ours and Stoeldraijer (2011) and Vandenberghe, Waltenberg and Rigo (2012) cannot control for the educational composition of the workforce.

[88] In the literature of production function estimation in the Hellerstein – Neumark framework, the first study applying the method proposed by Ackerberg, Caves and Frazer (2006) is the one by Konings and Vanormelingen (2010) analyzing the impact of training on productivity. The other study providing estimates by Ackerberg, Caves and Frazer (2006) and the first one to apply it in combination with firm fixed effects is Vandenberghe, Waltenberg and Rigo (2012).

3.2 Methodology

The empirical analysis uses the following variant of Cobb-Douglas production function:

$$\ln VA_{jt} = \beta_0 + \beta_1 \cdot \ln K_{jt} + \beta_2 \cdot \ln L_{jt} + \sum_k \gamma_k \cdot l_{k_{jt}} + \lambda \cdot X_{jt} + \varepsilon_{jt} \qquad (1)$$

Equation (1) includes on the left hand side the logarithm of value added as the output measure, while the right hand side variables are the logarithms of capital and employment denoted by ln$K$ and ln$L$, and the l_k worker shares defined as the proportion of workers in group k within the labor force of the firm. The worker share variables control for the gender, age and educational composition of the firm[89]. Specifically, the l_k variables in the basic specification are as follows: proportion female, proportion educated, proportion below the age of 35, proportion aged 45-55 and proportion over 55[90]. These share variables can be simply considered as separate inputs beside the more traditional capital and labor. The equation also includes controls for time, industry, region and ownership effects summarized by the matrix X.[91] Finally, ε is the error term.

Note that the above representation of the production function is a simplification of the one inspired by Griliches (1957) and later pioneered by Hellerstein, Neumark and Troske (1999) and Hellerstein, Neumark (1999). Though the aim of the current paper is not to obtain an estimate of the relative marginal productivities of the different worker groups, it is useful to get insight into the theoretical model behind equation (1) and see the relationship between relative marginal productivities as estimated by Hellerstein and Neumark, and the γ_k

[89] Though the database includes information on the occupation of the employees, I do not include occupational shares among the controls, as these controls may themselves depend on education/age, and may bias the estimates (Angrist and Pischke 2009).
[90] The reference categories are as follows: proportion male, proportion uneducated and proportion aged 35-45.
[91] X includes the interaction of 19 industrial categories and year dummies, 7 regions and ownership.

coefficients of equation (1). In their works of comparing the relative productivities and relative wages of different worker groups, Hellerstein, Neumark and Troske (1999) and Hellerstein and Neumark (1999) estimate production function including a labor quality variable instead of the traditional labor input. The labor quality variable (*QL*) serves to account for the different productivity contributions of the various worker groups. Assuming that the groups of workers are perfect substitutes, grouping workers into $n = 0, 1, \ldots, N$ categories, and denoting by L_n and φ_n the number and the economy-wide productivities of employees in group *n*, the *QL* term takes the following form:

$$QL = \sum_{n=0}^{N} \varphi_n L_n = \varphi_0 L_0 + \sum_{n=1}^{N} \varphi_n L_n = \varphi_0 L\left[1 + \sum_{n=1}^{N}\left(\frac{\varphi_n}{\varphi_0} - 1\right)\frac{L_n}{L}\right] = \varphi_0 L\left[1 + \sum_{n=1}^{N}\left(\frac{\varphi_n}{\varphi_0} - 1\right) l_n\right] \qquad (2)$$

Thus, the production function using (2) becomes:

$$\ln VA_{jt} = \beta_0 + \beta_1 \ln K_{jt} + \beta_2 \ln \varphi_0 + \beta_2 \ln L_{jt} + \beta_2 \ln\left[1 + \sum_{n=1}^{N}\left(\frac{\varphi_n}{\varphi_0} - 1\right) l_{n_{jt}}\right] + \lambda \cdot X_{jt} + \varepsilon_{jt} \qquad (3)$$

The coefficients of interest are the relative productivity parameters denoted by φ_n / φ_0. Since grouping workers into detailed categories requires estimating a large number of productivity parameters, two restrictions are usually applied to the labor quality term[92]. First, the number of coefficients to be estimated can be reduced by assuming that relative productivities are constant across other categories[93]. Second, the proportion of workers is assumed to be constant across other categories (e.g. the proportion of female employees is the same in each

[92] For example, grouping workers into two gender, three age, two educational and three occupational groups would require estimating 35 parameters (e.g. the group of female, young, educated, white collar workers, the group of female, young, educated managers, etc.). Both restrictions are widely applied in the literature based on the Hellerstein, Neumark (1999) methodology.

[93] This means that, for example, the gender productivity gap is the same among college and no college employees; or, the productivity difference between workers with and without degree is the same among male and female employees, etc. Though in certain cases this assumption may be too restrictive (e.g. gender gaps are probably different in the various occupational categories; or, the returns to education may be different among the different age groups), the same framework is widely applied in the earning regression context when using standard Mincerian earning regressions without interactions.

age category). Differentiating workers by gender, age (below 35, 35-45, 45-55, over 55) and education (degree, no degree), the production function using the above simplifications becomes (4):

$$\ln VA_{jt} = \beta_0 + \beta_1 \ln K_{jt} + \beta_2 \ln \varphi_0 + \beta_2 \ln L_{jt} + \beta_2 \ln\left[1 + (\varphi_F - 1) l_{F_{jt}}\right] + \beta_2 \ln\left[1 + (\varphi_E - 1) l_{E_{jt}}\right]$$
$$+ \beta_2 \ln\left[1 + (\varphi_{Y35} - 1) l_{Y35_{jt}} + (\varphi_{45\_55} - 1) l_{45\_55_{jt}} + (\varphi_{O55} - 1) l_{O55_{jt}}\right] + \lambda \cdot X_{jt} + \varepsilon_{jt}$$

where φ_F is the productivity of women relative to men, φ_E is the productivity of educated workers relative to uneducated workers, φ_{Y35}, φ_{45_55} and φ_{O55} are the relative productivities of the below 35, aged 45-55 and over 55 worker groups relative to those aged 35-45. The proportion of workers in each group are denoted by the l_k variables (*k = F, E, Y35, 45_55, O55*).

After linearization equation (4) becomes[94]:

$$\ln VA_{jt} = \beta_0 + \beta_1 \ln K_{jt} + \beta_2 \ln \varphi_0 + \beta_2 \ln L_{jt} + \gamma_F l_{F_{jt}} + \gamma_E l_{E_{jt}}$$
$$+ \gamma_{Y35} l_{Y35_{jt}} + \gamma_{45\_55} l_{45\_55_{jt}} + \gamma_{O55} l_{O55_{jt}} + \lambda \cdot X_{jt} + \varepsilon_{jt} \qquad (5)$$

Note that equation (5) is the same as the starting Cobb-Douglas specification of equation (1). Unlike in the nonlinear equation (4), the γ_k coefficients (*k = F, E, Y35, 45_55, O55*) in equation (5) can not be interpreted as relative marginal productivities. They can be simply thought as giving an idea about the contribution to value added of the different worker groups. More precisely, the γ_k coefficients can be considered roughly as elasticities: if l_k, the

[94] Assuming that e.g. $(\varphi_F - 1)\frac{L_F}{L} < 0.1$ holds, the linear approximation is:

$\ln\left[1 + (\varphi_F - 1)\frac{L_F}{L}\right] \approx (\varphi_F - 1)\frac{L_F}{L}$, and the following relationship holds between the worker share coefficients of equations (4) and (5): $\gamma(\varphi_F - 1) = \gamma_F$. Several studies following the work of Hellerstein, Neumark and Troske (1999) and Hellerstein and Neumark (1999) applied the linear approximation. Such studies include, e.g. Dostie (2011), Crepon et al (2006), Ours and Stoeldraijer (2011) or Vandenberghe, Waltenberg and Rigo (2012).

share of workers in group k within the firm increases by 1 percentage point, value added changes by γ_k percent. In the linearized equation (5) the relative marginal productivities can be computed by dividing the γ_k coefficients by the coefficient of the labor term, β_2, and adding one. As the paper concentrates on assessing how productivity is related to age, thus, obtains estimates of the γ_k parameters, I do not compute relative productivities. However, I often compare the obtained γ_k coefficients of the various categories with each other and interpret e.g. $\gamma_{Y35} > \gamma_{O55}$ as the younger age group being more productive than the older one. Thus, when I talk about the productivity of the different worker groups, I refer to the estimated γ_k parameters.

Assuming that the error term and the right hand side variables are uncorrelated, equation (1) can be consistently estimated via OLS. In this case input coefficients are identified using total variation, and an age group is estimated to be more productive than another group if a firm with a higher share of this age group in its labor force produces on average more than a comparable firm with a lower share of this age group (Ours and Stoeldraijer, 2011). However, researchers share the consensus that the presence of time invariant unobserved firm attributes yields in most cases biased OLS estimates (see e.g. Cardoso et al 2011, Cataldi et al 2011 or Vandenberghe et al 2012, among others). These firm fixed effects, such as the quality of the capital, the management practices of the firm or advantageous firm location, may be correlated both with firm-level productivity and its workforce composition resulting in spurious correlation between the two. For example, OLS estimates are upward biased if younger employees self-select themselves into more productive firms, e.g. they tend to work in firms with better management, more up-to-date technology[95]. Another likely phenomenon is that the share of older employees is disproportionately low in companies with better management and more up-to-date technology, which results in downward biased OLS estimates[96].

I will provide estimates taking into account firm fixed effects using three methods. One way to get rid of the time invariant unobserved heterogeneity is to demean the variables by subtracting their time averages: $x_{jt} \to x_{jt} - \frac{1}{T}\sum_{t=1}^{T} x_{jt}$. As the firm fixed effects are time invariant, they drop out. Running OLS on the transformed variables results in the Fixed Effects or within estimator[97].

Another solution is to difference the variables: one can use first-difference (FD) or longer difference (LD) and run OLS on the transformed variables[98]. Obtaining estimates on long-differenced variables also allows for the possibility that changes in age shares have a delayed impact on firm productivity (Cataldi, Kampelmann, Ryxc 2011)[99].

The choice between the various within-dimension methods, FE, FD and LD depends on many factors, e.g. on the assumptions of exogeneity[100]. However, when using regressors,

[95] Note that the direction of bias in the OLS estimates depends on the correlation between the omitted firm fixed effects and the included regressors, as well as how the omitted variables are related to the dependent variable.
[96] Self-selection of older workers into firms with older capital, outdated technology was found for example by Malmberg et al (2005) on Finnish data.
[97] The consistency of the estimator requires strict exogeneity, i.e. $E(x_{jt}, u_{js}) = 0$ for $s = 1, 2, \ldots, T$ where x_{jt} stands for the right hand side variables. The strict exogeneity condition rules out the presence of unobserved productivity shocks being correlated to the inputs (Eberhardt and Helmers, 2010).
[98] The differencing transformation is less demanding in terms of the exogeneity conditions. For example, the consistency of the FD estimator requires only that $E(x_{jt}, u_{js}) = 0$ for $s = t, t\text{-}1$, which is a weaker form of strict exogeneity (Eberhardt and Helmers, 2010).
[99] Usually it takes more time for the new personnel to learn the specificities of the firm.
[100] The choice between the various methods also depends on assumptions about the error term. For example, if u_{jt} is a random walk, then the FD estimator will be more efficient than the FE estimator as in that case the Δu_{jt} are serially uncorrelated. If u_{jt} is an error term with $u_{jt} \sim iid(0, \sigma_u^2)$, then the FE estimator will be more efficient as in this case Δu_{jt} exhibits negative serial correlation. However, under the null that the model is correctly specified,

which are likely to be measured with error (e.g. in the current case when worker share variables are computed based on a representative sample of the firms' workforces), one needs to bear in mind that within estimates will probably suffer to some extent from measurement error bias. Griliches and Hausman (1986) derived that the different ways of eliminating firm fixed effects implies different consequences for the extent of measurement error bias. They prove that the attenuation bias caused by the measurement error is largest in the case of the FD estimator, while the FE and LD estimators are less affected. Thus, the finding of FD estimates close to zero, while higher FE and LD estimates are suggestive that measurement error may be the reason for the low FD coefficients. My benchmark within-estimates are provided by FE, but I also show results using FD and LD for comparative purposes.

All the above methods ignore productivity shocks, which are not known by the econometrician, but observed by the firm, and the firm can react to these shocks by increasing or decreasing its inputs. The resulting simultaneity problem causes that estimates produced by the above mentioned techniques are biased. Thus, a complete representation of the error term includes both the firm fixed effects, productivity shocks and the noise parameter: $\varepsilon_{jt} = \alpha_j + \omega_{jt} + u_{jt}$. The simultaneity problem affects the age share estimates e.g. if the firm faces a negative productivity shock and reacts by not hiring new individuals or laying off newly hired and predominantly young employees, which causes the share of the older workforce within the firm increase. The negative correlation between the share of older employees and the output is then incorrectly interpreted by the researcher as older workers being less productive. Similarly, if firms hire more young people in case of a positive productivity shock, methods not taking care of the simultaneity issue interpret the positive

the FE, FD and LD estimators will differ only because of the sampling error (Wooldridge, 2002). A potential drawback of the differenced estimators is the loss of data.

association between the higher productivity and the higher share of younger employees as the younger age group being more productive. Thus, if adjustment to productivity shocks occurs by hiring or laying off predominantly younger employees, methods not taking care of the simultaneity overestimate both the positive effect of the younger and the negative productivity impact of the older employees. Note, however, that it is also possible that firms react to economic downturns by inducing early retirements. In that case, OLS and within estimates would incorrectly suggest a higher productivity of older workers.

I experiment with two methods to handle the simultaneity problem. One approach is to use instrumental variables. For an IV estimator to be consistent, the instrument z needs to be valid, or exogeneous: $cov(z, u) = 0$, and it must be relevant, or informative meaning that it must be correlated with the endogeneous regressor, conditional on all exogenous variables[101]. The validity of the instruments can be tested by the use of Sargan/Hansen tests of overidentifying restrictions[102]. Under the null hypothesis of joint validity, the test statistic is distributed as χ^2 with degrees of freedom equal to the degree of overidentification (Roodman, 2006). The failure to reject the null implies that instruments are valid assuming that there are enough valid instruments to identify the equation exactly. The validity of those instruments, which are necessary to exactly identify the equation cannot be tested as they will be orthogonal to the residuals by construction[103]. Thus, one can never be certain that the full set of instruments are valid, but the researcher should do as much as possible to get convinced

[101] Invalid instruments produce biased and inconsistent estimates that can be even more biased than the corresponding OLS estimates. Weak instruments, which are only weakly correlated to the endogenous regressor produce consistent estimates, but these estimates are almost certainly biased in finite samples (Murray, 2006).
[102] The Sargan's statistic is a special case of Hansen's J statistic under the assumption of homoscedasticiy.
[103] If the model is exactly identified, detection of invalid instruments is not possible as the estimator will choose $\hat{\beta}$ so that $Z'\hat{E} = 0$ exactly (Roodman, 2006).

that at least some of them are valid[104]. A simple and intuitive way to assess if instruments are informative is to run reduced form regressions with the endogenous variable on the left hand side and the instrumental variables on the right hand side (Murray, 2006). Then, one can get an idea about the relevance of the instruments by checking the estimated coefficients, if they are jointly relevant and looking at the R-square and Shea's partial R-square values[105].

In the ageing – productivity literature IV methods are the most common way to tackle the problem of unobserved productivity shocks. Aubert and Crepon (2006), Göbel and Zwick (2009), Ours and Stoeldraijer (2011), Cardoso, Guimaraes and Varejao (2011) estimate production function in a differenced form via GMM, and instrument the endogenous variables with the lagged values of the levels[106]. The underlying assumption is that shocks occurring between (t-1) and t are uncorrelated with the levels of inputs earlier than (t-2).[107] However, as illustrated e.g. by Blundell and Bond (2000), the above method may suffer from the weak instrument problem and often yields unsatisfactory estimates. This is especially true if the endogenous variables are close to random walk. In this case the differenced variables are

[104] Another tool to gain more credibility in the instruments is the use of Difference-Sargan/Hansen test, which can check the validity of a subset of instruments. Under the null of the joint validity of the full instrument set, the difference between the Sargan/Hansen test statistics of the estimations with and without the subset of instruments, is asymptotically distributed as χ^2 with degrees of freedom equal to the subset of instruments. Thus, a failure to reject the Difference-Sargan/Hansen test implies that the additional instruments are valid (Roodman, 2006).

[105] Stata's ivreg2 command with the ffirst option produces the reduced-form first-stage regressions regressing the endogenous variables on the full set of instruments. Shea's partial R-square takes the intercorrelation among the instruments into account, therefore, it is more appropriate than the simple partial R-square statistic. (Baum, Schaffer, Stillman 2003).

Some formal tests are also available to check the relevance of the instruments, for example the tests by Stock and Yogo (2005) and by Andrews, Moreira, and Stock (2006). Providing such formal tests is a fast evolving field of economics, and still a lot needs to be done. A detailed non-technical discussion of these tests can be found in Murray (2006).

[106] Note, however, that there are differences between the methods applied by Göbel and Zwick (2009) and the other studies. Göbel and Zwick (2009) uses the xtabond2 command of Stata performing the Difference-GMM procedure by Arellano and Bond (1991). On the other hand, the rest of the cited papers apply the ivreg2 command of Stata, which basically performs the Anderson-Hsiao (1981) difference estimator. One main difference between the two approaches is that Difference-GMM applies "GMM-style" instruments building a set of instruments and substituting zeros for missing observations (Roodman 2006). In this way, the number of observations is usually higher in the latter case.

[107] Aubert and Crepon (2006), Ours and Stoeldraijer (2011) include all lags equal and greater than 2, while Cardoso et al (2011) includes lags 2 and 3. Göbel and Zwick (2009) includes lags 3-8 of the age share variables.

dominated by the noise term, which causes that the lagged levels have a poor predictive power. System – GMM, an alternative procedure by Blundell and Bond (2000) supplements the differenced equations with their level version, and instead of eliminating fixed effects, uses instruments, which are orthogonal to them. The differenced equations use the same moment conditions as described above. In the level equations, the endogenous variables are instrumented by their lagged first differences. System – GMM has the advantage to use also the cross-sectional variation in data, thus, the downward bias due to measurement error may be less severe. Göbel and Zwick (2009) and Vandenberghe, Waltenberg and Rigo (2012) provides estimates of the age-productivity profile using System – GMM. However, System – GMM estimates may also suffer from weak identification. Dostie (2011) refers to Gorodnichenko (2010) who proves using Monte Carlo simulations that the Blundell and Bond (2000) estimator is in general weakly identified. The weak identification problem may be even more relevant when one estimates production function using worker composition variables. As in most cases workers are sampled within the firms, the age share variables are likely to be computed with some measurement error. As Dostie (2011) notes, this reduces the year-by-year correlations between current and lagged age shares.

In the empirical analysis I experiment using all the above described IV – GMM methods. I perform several diagnostic checks to examine the reliability of the results. Following Blundell and Bond (2000), I check if the variables are close to unit root by running simple AR(1) regressions on each variable. Highly persistent variables may indicate that the lagged levels are weak instruments of the first differenced variables. Then, similarly to Blundell and Bond (2000) and Murray (2006), I examine the explanatory power of the various instrument sets by running reduced form regressions, and checking the F-statistic and R-square statistic[108]. The validity of the instruments is tested by the use of Hansen test for overidentifying restrictions.

The diagnostic tests suggest in general high persistence in the variables, and better explanatory power for the level regressions relating the level variables to the lagged differences. These results are indicative that the System – GMM estimator may yield more appropriate estimation results than the Difference – GMM specification. However, the overidentifying restrictions are rejected in all System – GMM specifications using various lag structures. Thus, in the Results section I only present the specification passing Hansen's overidentification test. The reported IV – GMM estimates follow the approach applied also by Aubert and Crepon (2006), Ours and Stoeldraijer (2011), or Cardoso, Guimaraes and Varejao (2011)[109].

Another strand of the literature takes a structural approach to handle the simultaneity issue. Authors of this literature (Olley and Pakes, 1996, henceforth OP; Levinsohn and Petrin, 2003, henceforth LP; Ackerberg, Caves and Frazer, 2006, henceforth ACF) suggests controlling for the omitted unobserved productivity term ω_{jt} by using the observed input decisions of the firm. OP proposes using the investment decision of the firm to proxy the unobserved productivity, while LP and ACF apply intermediate inputs (e.g. material costs, energy) to control for the missing component. In the paper I perform the methods by LP and ACF, and use material costs to proxy unobserved productivity. A detailed discussion of both methods is provided in the Appendix. Below, I summarize the most important steps and assumptions.

[108] The output of the above diagnostic tests are provided in the Appendix, see Tables 3.8. and 3.9.
[109] I use the ivreg2 command of Stata with the gmm2s option. First-stage reduced regressions are performed using the ffirst option. Hansen's J test and two Kleibergen-Paap statistics to test under-identification and weak identification are automatically reported by the program. To test the endogeneity of the regressors, the endog option is used.

To proxy the unobserved productivity, LP use the intermediate demand function of the firm: $int\_goods_{jt} = f(\omega_{jt}, k_{jt})$. Assuming that the intermediate inputs are strictly increasing function of ω_{jt}, the demand function can be inverted to obtain a proxy for the unobserved productivity: $\omega_{jt} = g(\ln K_{jt}, \ln M_{jt})$. LP identifies the age share coefficients based on the following equation:

$$\ln VA_{jt} = \beta_2 \cdot \ln L_{jt} + \sum_k \gamma_k \cdot l_{k_{jt}} + \lambda \cdot X + \Psi(\ln K_{jt}, \ln M_{jt}) + \varepsilon_{jt} \qquad (6)$$

where the term $\Psi(\ln K_{jt}, \ln M_{jt}) = \beta_0 + \beta_1 \cdot \ln K_{jt} + g(\ln K_{jt}, \ln M_{jt})$ includes the $g(\ln K_{jt}, \ln M_{jt})$ proxy function of the unobserved productivity and the capital term of the production function as it cannot be identified separately due to collinearity issues. I estimate equation (6) approximating $\psi(.)$ by third order polynomials. Running OLS on (6) removes bias associated with the unobserved productivity term. Besides, I provide results by estimating (6) using demeaned variables, which tackles the issues of both heterogeneity and simultaneity. In the ageing and productivity literature Hellerstein and Neumark (2004), Dostie (2011) and Vandenberghe (2011) used LP on cross-sectional data. Introducing firm fixed effects into the equation (6) was applied only by Vandenberghe (2011).

ACF questions the validity of (6) noting that neither the capital nor the labor coefficients may be identified due to collinearity issues. As labor and material costs are both perfectly variable inputs in the LP model and chosen simultaneously, they are probably allocated in a similar way. Thus, labor is likely to be determined by the same state variable ω_{jt} as the intermediate input, therefore, it does not vary independently from the $g(.)$ proxy function. As a consequence, neither the labor nor the share coefficients can be identified in the first stage. ACF suggests netting out only the noise parameter in the first step, and identifying all input coefficients in the second stage. Thus, ACF first estimates equation (7):

$$\ln VA_{jt} = \Psi(\ln K_{jt}, \ln M_{jt}, \ln L_{jt}, l_1, ..., l_k, ...) + \varepsilon_{jt} \qquad (7)$$

where $\Psi(\ln K_{jt}, \ln M_{jt}, \ln L_{jt}, l_1, ..., l_k, ...) = \beta_0 + \beta_1 \cdot \ln K_{jt} + \beta_2 \cdot \ln L_{jt} + \sum_k \gamma_k \cdot l_k + \omega_{jt}$.

I estimate equation (7) by using a third-order polynomial approximation of the $\psi(.)$ function. The aim of the first stage is to separate the error term from the unobserved productivity and to obtain predicted values of $\hat{\Psi}_{jt}$. These predicted values will be used in the second stage to model the unobserved productivity. Using the assumption that productivity follows a first order Markov process, it can be written as follows:

$$\omega_{jt} = E\lfloor \omega_{jt} \mid I_{jt-1} \rfloor + \xi_{jt} = E\lfloor \omega_{jt} \mid \omega_{jt-1} \rfloor + \xi_{jt} = g(\omega_{jt-1}) + \xi_{jt} \qquad (8)$$

where ζ_{jt} represents the innovation in productivity. Assuming that capital is decided at period (t-1), it is uncorrelated with the innovation in productivity. Furthermore, assuming that the labor inputs (including the age shares) are decided between periods (t-1) and t, their (t-1) value is uncorrelated with the innovation in productivity. Consequently, the identifying moment conditions are as follows:

$$E\left[\xi_{jt} \mid \begin{array}{c} \ln K_{jt} \\ \ln L_{jt-1} \\ l^1_{jt-1} \\ \vdots \\ l^k_{jt-1} \end{array} \right] = 0 \qquad (9)$$

As ACF notes, the researcher may alternatively assume that the labor inputs were chosen at or prior to $t-1$. This is the case for example if labor markets are rigid[110]. Hence, an alternative set of identifying moment conditions uses all the current values of the inputs:

$$E\left[\xi_{jt} \mid \begin{matrix} \ln K_{jt} \\ \ln L_{jt} \\ l_{jt}^{1} \\ \vdots \\ l_{jt}^{k} \end{matrix}\right] = 0 \qquad (10)$$

The inclusion of firm fixed effects into ACF's model requires modifications only of stage one. In this case, the aim of the first stage is to net out both firm fixed effects and the noise term. Estimating equation (7) via FE estimator, one can obtain predicted values of $\hat{\Psi}_{jt}$, net of the noise term and the firm fixed effects. From here on, the procedure is analogous to the one described previously. As Vandenberghe, Waltenberg and Rigo (2012) discusses, including firm fixed effects into stage one increases the chance of verifying the monotonicity assumption, which is required to invert out ω_{jt}.[111] In the worker composition – productivity literature Konings and Vanormelingen (2010) is the first one to apply ACF on cross-sectional data, while the only study identifying the age share coefficients based on the ACF – firm fixed effect approach is the one by Vandenberghe, Waltenberg and Rigo (2012).[112]

In the paper I estimate equation (1) first by cross-sectional methods: OLS, LP and ACF. Then, within-estimates: FE, FD and LD are provided. The final set of estimates tackles

[110] Konings and Vanormelingen (2010) in their paper assessing the impact of training on productivity and wages uses moment conditions with timing assumptions similar to (16). They assume that material input is chosen after labor input and training "which seems plausible for an economy with rigid labor markets like Belgium".
[111] The authors refer to the stylized fact that firm fixed effects capture a large fraction of total productivity variation (Syverson 2011) implying that firms with similar material cost, capital and labor input values may have very different values of ω_{jt}.
[112] The ACF procedures are implemented in Stata11 using the moment evaluator version of the gmm command. I thank Stijn Vanormelingen and Jozef Konings for assisting with the first steps in programming the structural approach by ACF (2006).

both simultaneity and firm heterogeneity and includes IV-GMM and LP and ACF in combination with firm fixed effects.

3.3 Previous results

The empirical evidence regarding the age-productivity profile of the firms is mixed. Cross-sectional results usually imply hump-shaped profile. The estimated coefficients are mostly significant with small standard errors. But these estimates tend to be biased due to the reasons outlined in the Methodology section. Within estimates do not suggest a uniform profile, and the precision of the estimates is much smaller than in the cross-sectional dimension, which makes it harder to draw firm conclusions from the results.

Hellerstein, Neumark, Troske (1999) and Hellerstein and Neumark (2004) using 1990 cross-section data from US finds that the productivity of older workers (aged 55 and over) is lower compared to younger employees[113]. Dostie (2011) using Canadian data from 1999-2005 and Levinsohn and Petrin's (2003) method to correct for the simultaneity bias finds in general decreasing productivity for workers after the age of 55. However, these studies are based on cross-sectional data, and do not take into account unobserved firm heterogeneities.

Panel studies by Göbel and Zwick (2009) on German data and Ours and Stoeldraijer (2011) on Dutch data do not find evidence of decreasing productivity with age. Both papers eliminate firm fixed effects via first differencing, and handle the simultaneity problem by the use of internal instruments. Ours and Stoeldraijer (2011) estimates the production function in

[113] The two studies are based on different data sets. Hellerstein, Neumark, Troske (1999) uses the Worker Establishment Characteristic Database (WECD), while Hellerstein and Neumark (2004) uses the 1990 Decennial Employer Employee Dataset, which is much larger and more representative than the WECD.

differenced form and uses past levels of the inputs as instruments[114], while Göbel and Zwick (2009) provides estimates using both the Difference-GMM and the System-GMM approaches including two lags of the dependent variable besides the traditional regressors[115]. Both papers find an inverse U-shape age – productivity profile with peak at age 35-40 in the OLS estimates; essentially flat age – productivity profile in the FE case, while instrumental variable approaches imply an increasing age – productivity profile with younger workers being less productive than prime age employees. The precision of the IV estimates is particularly small in both studies: though the magnitudes imply an increasing age-productivity profile, none of the estimates are significant at the 5 percent level.

Similarly, Cardoso, Guimaraes and Varejao (2011) do not find evidence of decreasing productivity at later ages. Using Portuguese data from 1986-2008, the authors document increasing productivity until the age of 60 in their preferred IV-GMM specification. Their OLS estimates show the usual hump-shaped pattern. FE results imply decreasing productivity already from the age of 30. Comparing these results to the IV-GMM estimates, the authors conclude that methods failing to take into account the simultaneity problem, severely underestimate older workers' productivity.

Aubert and Crepon (2006), using Difference – GMM as their preferred specification, finds that the productivity of French workers increases until the of age 40-45, then it is quite stable with a small drop after 55. Comparing OLS, within-firm and GMM estimates, the authors conclude that both selection along unobservables, as well as the simultaneity between

[114] Their approach is similar in spirit to the Difference-GMM approach by Arellano and Bond (1992). However, AB(1992) uses „GMM-style" instruments, substituting zeros for missing observations and generating separate instrument for each lag and time period instrumented.

[115] Following Blundell and Bond (2000), they start with a specification of AR(1) productivity shocks. This model results in estimating a production function with the lagged dependent variable and lagged inputs as regressors besides the usual input variables. The parameters of the underlying production function are implied by common factor restrictions and can be tested. As these restrictions are clearly rejected, they do not consider it as a correct specification, and opt for including only the lagged dependent variable among the usual regressors.

the age structure of the workforce and unobserved productivity shocks play an important role in biasing the coefficient estimates. Contrast to Göbel and Zwick (2009) and Ours and Stoeldraijer (2011), their OLS estimates show that the productivity of the 25-29 age group is the highest. Productivity decreases until age 40-44, then, in the later ages it rises again[116]. The within-estimates result in an inverse U-shaped age-productivity profile having the peak around the age 35. Comparing OLS and within-firm estimates they conclude that OLS estimates are biased by the systematic selection of older workers into "older, more-capitalistic, and thus more productive firms". The GMM estimates highlight that the productivity of the older worker group is underestimated in the within dimension due to the behavior of the firms that they adjust to productivity shocks by hiring and laying off young employees. The GMM estimates imply that productivity increases until age 40-45, then it is quite stable with a small drop after 55[117].

Cataldi, Kampelmann and Rycx (2011) using Belgian data from 1999-2006 finds decreasing productivity for workers aged 50 and over in their preferred first-differences and long-differences specifications. Using another Belgian dataset, Vandenberghe, Waltenberg and Rigo (2012) also documents that the productivity of older employees is significantly lower compared to prime age workers. Their study provides results using both System – GMM and ACF's structural approach. The latter method is applied in the cross-sectional and within dimensions. Estimates obtained by System – GMM and ACF's structural approach are remarkably close to each other and imply that a 10%-points rise in the share of older workers decreases productivity by 2.2 – 2.7 %. Comparing these estimates to the simple FD case, the

[116] More precisely, they find that productivity increases after 44 until age 54, but their results are inconclusive as for what happens after age 55 due to the low precision of the parameter estimate.
[117] It is hard to draw conclusions as for what happens after 55 due to the large standard error of the estimates.

authors conclude that in Belgium adjustment to negative productivity shocks occurs primarily by laying off the older workforce (e.g. by inducing involuntary early retirement)[118].

The empirical evidence for the Hungarian economy is rather limited. Kertesi and Köllő (2002) analyzing how the experience-related wage gap changed after the regime change, showed that return to experience decreased after 1992, especially among the highly skilled. Comparing these developments to changes in productivity, the authors found that the decline in wage returns is in line with productivity differences between the younger and older workers differentiated by their level of skill. Following a similar logic, Chapter 2 of the thesis examines how the productivity of more experienced employees were affected by the technological, organization change after the regime change, and studied how long it took for more experienced workers to adapt to the new situation. To carry out the exercise, workers are grouped into two age groups: below and over the age 45, and their relative productivity is estimated in five distinct periods covering the years 1986-2008. The authors found that the relative productivity of older employees – primarily of those with higher level of education – decreased substantially after the regime change in line with the inflow of modern capital. However, by the most recent years, the relative productivity of older workers were not below the productivity of younger employees suggesting that skill obsolescence is not an acute phenomenon any more. Besides the above studies, there are no papers addressing the issue of how firm-level productivity is related to the age composition of the workforce in Hungary. Moreover, studies defining detailed age intervals and estimating the age – productivity profile of firms are missing. The current study plans to fill in this gap.

[118] The coefficient estimate (productivity of workers aged 50-64) in the first-differenced (FD) case is -0.11, while in the System – GMM and ACF+FD cases the estimates are much lower, -.027 and -0.22, respectively.

3.4 Data

The Hungarian Wage and Employment Survey (WES) is a large representative linked employer-employee database available for the years 1986, 1989, and 1992-2005. To avoid biases coming from the likely structural break after the regime change, I only use the years from 1992. The database includes information on all tax-paying legal entities with double-sided balance sheets that employed at least 20 employees in 1986, extended to firms with at least 10 workers in 1995, and from 1999 on to micro-firms as well. Within firms, workers are randomly sampled[119]. On average, 6.5 percent of the production workers and 10 percent of the non-production workers is covered by the database.

The linked database includes demographic information on employees as well as information on the firms where they are employed. Worker variables include the gender, age, highest education level (five categories: less than 8th grade, elementary, high school, vocational, university), and occupation (4 digit occupational code). In the baseline models, I constructed the worker share variables by grouping employees into four age categories (under 33, 35 – 45, 45 – 55, over 55), two educational categories (degree – no degree), and into gender groups. The firm variables used in the estimation are value added (defined as sales minus material costs), capital, material costs, employment, industry, region, size, and ownership.

The original WES database includes 36,507 firms with 137,460 observations. In order to minimize measurement error in the worker share variables, I kept only those firms, which have at least five employees surveyed each year. The resulting sample is composed of an

[119] From 1992, workers were selected into the sample based on their date of birth: production workers were included if their birth date fell on either the 5th or the 15th of any month, and non-production workers if being born on the 5th, 10th, or 15th of a month.

unbalanced panel of 28,489 firms with 91,642 firm-year observations. Table 3.1 provides detailed information on the output and the traditional input variables of the firms (employment, capital, material costs). The detailed descriptive statistics of the worker share variables are shown in Table 3.2. To get a more accurate picture of the identification possibilities across the different specifications, both the level and the within-transformed variables are included in the tables. For example, the first row of Table 3.2 shows that the share of employees aged below 35 is 35.6 percent, on average. The second row displays the mean differenced version of the variable indicating the deviation from the firm average; hence, we expect smaller standard deviations and a mean around zero. This is confirmed by the numbers: mean around zero and the standard deviation is 0.107. The third row shows the one-year changes, i.e. the variable in first differenced form. Again, we expect a mean around zero and small variation. The mean is -0.012 (which means that the mean change is -1.2 percentage points) and the standard deviation is 0.131. Finally, the fourth row displays the variable in long differenced form, i.e. three – year changes. We expect somewhat larger standard errors than in the mean differenced and first differenced case, and again a mean around zero. Correspondingly, the numbers show that the mean change is -3 percentage points and the standard deviation is 0.168, which is only a bit smaller than in row 1 for the levels.

Comparing the statistics displayed by Tables 3.1 and 3.2 gives an insight into the differences in the behavior of the traditional input variables of capital and labor and the worker shares, which were found to be estimated with less precision in the within dimension by previous studies. First, the within transformed capital and labor have larger variances than the worker share variables[120]. These forecast the possibility that the share variables may be more prone to measurement error, therefore, estimates may be more biased in the within dimension than the traditional capital and labor input variables. Comparing the within-estimates via FE, FD and LD will give some insight into the issue.

3.5 Results

3.5.1 Baseline results

First, I estimate equation (1) via cross-sectional methods: OLS, LP and ACF. Then the first group of within-estimates taking into account only unobserved firm heterogeneity is presented. The last set of estimates tackles both the heterogeneity and simultaneity issues and includes IV-GMM, LP+FE and ACF+FE techniques. Figures 3.1., 3.2. and 3.3. give a graphical illustration of the firms' age – productivity profiles across the various specifications, while the full set of estimation results are summarized by Table 3.3.

Cross-sectional estimates imply decreasing age – productivity profile: workers aged below 35 are the most productive, and productivity decreases gradually from this age. OLS estimates suggest that increasing the share of workers above 55 (relative to the reference group of workers aged 35-45) by 10 percent suppresses firms' value added by 3 percent. The productivity differential between the youngest and oldest worker group is even larger: the OLS coefficient estimate on "workers over 55" relative to "workers below 35" is -0.434. The comparison of OLS, LP and ACF results reveals that the estimates are remarkably close to each other. LP shows the smallest productivity disadvantage for workers over 55 (point

[120] While the mean of all the within – transformed variables is around zero, the standard errors of the output, capital, labor and material costs variables lie in the range of 0.2 – 0.7, while for the age share variables they are smaller than 0.2.

estimate of -0.173), but the difference compared to OLS and ACF (point estimates of -0.3 and -0.24) is small. The result of somewhat smaller productivity drawback for older employees after taking into account the simultaneity between input and output choices is in line with earlier findings (e.g. Aubert and Crepon 2006, Cardoso et al 2011).

The coefficient estimates of capital and labor show a more diverse picture across the estimation methods. The structural estimator by LP produces higher capital and much lower labor coefficient relative to the OLS case: the capital coefficient increases to 0.356, and the labor coefficient drops to an unusually low value of 0.55. This pattern of the capital and labor coefficients between the OLS and LP methods is similar to the one found by Eberhardt and Helmers (2010) using a sample of UK high-tech firms from 2000 – 2007. They claim that the implausibly low labor coefficient of 0.2 found by them on the UK data seems to justify ACF's reasoning that the labor coefficient in the first stage of the LP procedure may not be identified due to collinearity problems. Though the labor coefficient estimated on the Hungarian data is not as unreasonably low as found by the above authors, it is lower than expected and casts doubt on the validity of the assumptions behind the LP model[121]. The capital and labor coefficients implied by ACF are very close to the OLS results. As expected, after taking into account unobserved productivity shocks, the labor coefficient slightly drops (from the OLS estimate of 0.8 to 0.76 in the ACF specification). Similar pattern was experienced by Eberhardt and Helmers (2010) showing that the ACF estimates are indeed within the OLS 95 percent confidence intervals.

[121] ACF (2006) comparing the relative performance of the OLS, LP and ACF estimators on Chilean data also finds a probably downward biased, but significantly positive labor coefficient. They list several explanations for it. For example, it is possible that the non-parametric approximations are not working well. Or, there are measurement errors in the proxy variables. Or, it is possible that the data generating process behind the labor variable is such that the collinearity problem does not arise.

The first set of within methods taking into account only unobserved firm heterogeneity (FE, FD, LD) imply that the productivity disadvantage of older workers is smaller than suggested by the cross-sectional estimates. Though aging is associated with decreasing productivity, the profile is less steep or almost flat depending on specification. FE estimates imply that increasing the share of older workers by 10 percentage point relative to the reference category of workers aged 35-45 decreases value added by 2 percent. The FE point estimate on “workers over 55” relative to the youngest group is -0.28, which is much smaller than in the OLS case (-0.43). Comparing OLS and FE estimates suggests that older workers may be overrepresented in firms with lower productivity, while younger employees may be systematically selected by better firms. LD estimates show an even more compressed age-productivity profile with the youngest workers being significantly more productive than the reference group, and productivity stays at a constant level after age 35. The LD point estimates imply that increasing the share of workers below 35 by 10 percentage point increases value added by 0.6 percent. The third method in this group, FD produces essentially flat age – productivity profile with all the age share coefficients around zero. These results are indicative of measurement error biasing more the FD estimates than the FE or LD coefficients as pointed out by Griliches and Hausman (1986). Both the labor and capital coefficients are smaller in the within than in the cross-sectional specifications: the capital coefficient is around 0.1 in all cases, the labor coefficient is around 0.7 in the FE and LD cases, and somewhat smaller, 0.56 in the FD specification.

The final set of results also suggest decreasing age – productivity profile, but in most cases an even more compressed profile appears than previously. The point estimates of the relative productivity of workers over 55 relative to the reference category (workers aged 35-

45) are remarkably close to each other in all three specifications: around – 0.17 in the LP+FE and ACF+FE cases, and -0.13 in the IV – GMM case, though this latter value is not significant. On the other hand, the coefficient on "workers below 35" shows substantial variation between the IV and structural approaches. The point estimate is 0.313 as implied by IV-GMM, while both LP+FE and ACF+FE suggest a coefficient estimate of around 0.06. Note, however that all the IV-GMM results are estimated with relatively large standard errors. Besides, the diagnostic tests are indicative that the internal instruments are weak[122]. Therefore, IV-GMM estimates should be considered with this caveat in mind, and the results could be cautiously interpreted as suggestive of decreasing productivity with age, with possible drops of productivity at the ages of 35 and 55. Thus, apart from the IV-GMM results, all the other methods handling the heterogeneity and simultaneity issues deliver very similar age share estimates. The finding of smaller productivity advantages for the young, and smaller productivity disadvantages for the older worker group than in the FE case suggests that a likely attitude of the firms to adjust their workforce to productivity shocks is dominantly a recruitment freeze. However, FE and LP+FE, ACF+FE age share point estimates are remarkably close to each other. Thus, the omitted variable of unobserved productivity do not biases FE results to a large extent.

[122] Though in the first stage reduced form regressions (examining the relevance of the instruments) the joint significance of the regressors is not rejected in any case, the low value of the Shea partial R-square statistic suggests that instruments have weak explanatory power. The weak instrument problem is also highlighted by the reported Kleibergen-Paap under-identification and weak identification statistics. Note that the endogeneity tests are built on the prerequisite of having strong instrumental variables. In the presence of weak instruments not much is known about their behavior, and the result that the endogeneity test cannot reject the exogeneity of the age share variables may be interpreted as the consequence of poor instruments, which causes that the test fails to detect that the age share variables are truly endogenous (Tchatoka and Dufour 2010). For more details on the performance of endogeneity tests in the presence of weak instruments see Tchatoka and Dufour (2010).
I have tried several specifications using various lag structures, but none of them passed all the diagnostic tests (validity and relevance). The reported estimates yield relatively the best performance among the IV-GMM specifications, but suffer from the weak instrument problem.

The capital and labor coefficients show the expected variation across the methods. ACF+FE and IV-GMM labor estimates are very close to the FE results, around 0.7, but the IV-GMM estimate has a large standard error. The LP+FE labor estimate is – as expected - much smaller.

Thus, the results so far give indication of a decreasing age – productivity profile in Hungarian firms. The relative productivity of the oldest worker group to those aged 35-45 is around – 0.17 in the specifications taking into account both heterogeneity and simultaneity. Productivity decreases at the ages of 35 and 45, and there is a small drop after 55. The results are also indicative that measurement error may bias the estimates as suggested by the comparison of FE, FD and LD estimates. This is a likely problem in all exercises estimating production function augmented with worker composition shares, as the share variables are usually computed from a sample of workers within the firm (see e.g. Dostie 2011). The estimation results also suggest that both selection and the simultaneity problem bias the benchmark OLS results, and the selection issue seems to have more importance in the Hungarian case.

3.5.2 Robustness analysis

Though the above results uniformly point to a decreasing age – productivity profile, I carried out further robustness checks to see if the results hold for (a) more detailed age groups, (b) shorter periods, (c) separately for manufacturing and services samples. These robustness checks are performed using only the benchmark OLS and the well-performing within-methods: FE and LD from the first group of within-techniques and LP+FE, ACF+FE from the second group[123]. Finally, as an extension of the current results, I try to give some insight into the relationship between the firms' age – productivity and age – wage profiles.

As a first step, I re-estimated equation (1) grouping workers into eight age categories: younger than 25, aged between 25-30, 30-35, 35-40, 40-45, 45-50, 50-55 and over 55. Graphical representation of the age – productivity profiles is now provided by Figure 3.4, and estimation results are summarized by Table 3.4.[124] Similarly to previous studies, OLS produces now a hump-shaped productivity profile: productivity peaks at the ages of 25-35, and gradually declines afterwards. On the other hand, FE shows exactly the same pattern as the previous analysis with less worker groups: productivity drops at the ages of 35, 45 and 55. The coefficient estimates on worker groups younger than 35 are statistically not different from each other, and the same is true for worker groups aged between 35 and 45. The LD results have slightly different indication as previously: the coefficient estimates on "workers younger than 25" and "aged 25-30" are not significantly different from the productivity of the reference group, while workers aged 30-35 have significantly higher productivity from the reference workers aged 35-40[125]. Over the age of 40 the productivity profile is essentially flat, which is the same as indicated previously. Similarly to the FE case, LP+FE produces results identical to those obtained with less worker categories. On the other hand, ACF+FE suggests declining productivity only over 50, while previous analysis indicated a drop of productivity at age 45. Comparing the results across the various econometric specifications, the same

[123] Remember that FD estimates were likely to be severely downward biased implying essentially zero age-share coefficient estimates. IV-GMM results are in line with expectations, but instruments were found to be weak, thus, estimates are likely to be biased.
[124] Note that the ACF+FE specification does not include controls for the gender and the educational composition of the firm. The reason is that the much larger number of parameters (seven age groups, capital, labor, material costs) make the optimization procedure complicated and imprecise. However, FE and LD estimates with and without gender and educational controls are very close to each other.
[125] Note, however, that the coefficient estimates on worker groups younger than 25, aged between 25-30 and 30-35 are not significantly different from each other.

conclusion holds as previously: the age – productivity profile gets more and more compressed moving from OLS towards FE and LP+FE, ACF+FE, and the productivity disadvantage of older employees is the smallest using the latter two methods. Comparing the results with detailed age categories to those using less worker groups in the previous analysis, suggests that the classification of workers into the four groups of below 35, aged 35-45, 45-55 and over 55 is likely to be a good assumption. The differences in the age-productivity profiles in the two cases are small. OLS and LD implies that the productivity of the youngest worker group below 25 may be somewhat smaller than the productivity of workers aged 30-35, and ACF+FE suggest a drop in productivity only after the age of 50, but FE and FE+LP produces identical profiles as previously.

As a second robustness check, I repeat the exercises splitting the sample into two distinct periods: 1992-2000 and 2001-2008. The long panel used in the analysis so far is appealing from several reasons. First, it may offer more variation in the data, which is crucial for identification, especially in the within dimension. Second, IV and LD estimations require the use of lags that may result in a substantial loss of observations. Third, as discussed by Cardoso, Guimaraes and Varejao (2011), in studies based on short panels, identification is mostly based on the turnover of workers. On the other hand, having a long panel, identification may be enhanced additionally by observing workers moving from one age bracket to another one[126]. Though these advantages are clearly relevant, the assumption of no structural break over the 17 years considered may be problematic in the Hungarian case. As discussed by Kertesi and Köllő (2002), Kézdi (2002) and Chapter 2 of the thesis, older employees experienced a large devaluation of their labor market skills earned before 1990.

[126] As pointed out by Cardoso et al (2011), the relative importance of this advantage depends on the distribution of workers inside the age brackets. However, having a 17-year panel and 10- and 5-year age brackets, the chances of using this additional source of variation in the data are larger.

This phenomenon, termed as skill obsolescence, resulted in a sharp decline of experience among the highly skilled employees after the regime change. Chapter 2 of the thesis documents that skill obsolescence is less and less relevant in most recent years, and finds no productivity gap between those aged less than or over 45 in 2006-2008[127]. Thus, there is good reason to believe that age – productivity profiles change during 1992-2008: the productivity disadvantage of older employees is likely to be larger in the first years after the regime change, as during this time, older employees had to cope with skill obsolescence besides the natural deterioration of their skills. Based on the economic developments in Hungary as discussed in Section 2.2.1. of Chapter 2, I define the first period covering the years of transitional recession and stabilization, 1992-2000, and the second period covers the years around the EU accession, 2001-2008[128]. This period is characterized by growing macroeconomic imbalances and steps for fiscal consolidation. Results for the separate periods are presented by Table 3.5. In line with expectations, the productivity disadvantage of older employees relative to the younger ones is smaller after 2000 in most specifications. The change in coefficients between the two periods is especially remarkably in the FE, LP+FE and ACF+FE specifications. Unfortunately, as implied by the much smaller number of observations, larger estimated standard errors and essentially flat age – productivity profiles, identification possibilities are much weaker in the LD case compared to the previous analysis using the long panel. Thus, in what follows, I focus the interpretation on the FE, LP+FE and

[127] As Chapter 2 documents, the above 45 / below 45 productivity gap narrows gradually from 1992, starting from the value of -0.096 in the period of 1992-1995. By 2001-2005, the gap is -0.054 and is significant only at the 10 percent level, while it totally disappears by 2006-2008 (see Table 2.6 of Chapter 2).

[128] Though Chapter 2 splits the panel of 1992-2008 into four distinct periods, due to the larger number of estimated parameters and the sensitivity of some of the estimation methods to the sample size used in the current Chapter, I decided to split the sample only into two periods. As found by Chapter 2, these periods largely correspond to the (1) years when the above 45 / below 45 productivity gap was large and significant, and (2) to those years when the gap is smaller in magnitude, less significant and finally decreases to zero. Both LD and the ACF technique proved to be sensitive to decreasing the number of observations.

ACF+FE cases. The first-period age share coefficient estimates in the FE case are very close to the full-sample results and show the familiar pattern from the previous analysis: significant drop of productivity at the ages of 35, 45 and 55. In the second period workers below 35 are still estimated to be the most productive, but workers over 45 do not have significantly lower productivity than the reference group of employees aged 35-45. LP+FE estimates are quantitatively close to the FE results, but in the second period the productivity profile is flat through the whole age interval. ACF+FE results have similar implication: the productivity disadvantage of older workers relative to the younger ones disappears after 2000, and similarly to LP+FE, the age-productivity profile is essentially flat in the second period. These findings are in line with conclusions from Chapter 2 and a priori expectations that skill obsolescence is less and less important in the more recent years as newer cohorts with better suited skills replaced workers in the older age group. The comparison of these results to those obtained in Chapter 2 is not straightforward due to the differences in estimation method, worker groups and the less detailed period subsamples. The FE and FE+LP estimates of the restricted model in Chapter 2 (see Table 2.6 in Chapter 2) give the best reference for comparison. Chapter 2 documents an over 45 / below 45 productivity gap (FE) of -0.096 and -0.067 in 1992-1995 and 1996-2000, respectively. On the other hand, the first period results of the current chapter reveal that productivity drops significantly at the ages of 35, 45 and 55. Regarding the years after 2000, Chapter 2 documents a productivity gap of -0.054 in 2001-2005 and an insignificant gap of -0.037 in the final period. The current chapter additionally implies that in 2001-2008 the gap is due to the higher productivity of the below 35 worker group. Thus, while the division of workers into two worker groups is well-suited to analyze the long-term impact of skill obsolescence[129], grouping workers into detailed groups reveals a more subtle age – productivity profile.

The third set of robustness checks examines if results are substantially different on the samples of manufacturing and services firms[130]. As outlined in the introduction, the age-related depreciation of productivity may vary across occupations depending on the relative importance of physical, cognitive and verbal skills. For example, physical abilities are probably more important in the manufacturing sample, while verbal abilities are likely to be the dominant dimension of skills in the services sample[131]. Results are presented by Table 3.6. The decreasing pattern of the age – productivity profile holds for all subsamples, but the magnitude of the drop at certain ages is slightly different across the samples. OLS estimates show much larger productivity decline at later ages in the manufacturing sample compared to services. After taking into account firm fixed effects, the profiles after the age of 35 are almost very similar across the subsamples, but the youngest worker group is found to be more productive within manufacturing firms. This is in line with a priori reasoning and the arguments raised by Skirbekk (2004) pointing to earlier decreases in productivity in occupations requiring physical abilities, while verbal abilities were found to be quite stable throughout working life. Comparing OLS and FE estimates reveals that younger workers may

[129] In Chapter 2 workers are grouped into two age categories following Kertesi and Köllő (2002) documenting that workers having already 15-20 years of pre-transitional experience were faced with the devaluation of their skills. In Chapter 2 our aim was to follow how the productivity of the worker group, which was most severely hit by the devaluation of their skills, evolved over time. Note also that grouping workers into more and more detailed worker groups, and defining smaller and smaller subsamples, increases data demands, and may lead to imprecise estimates. To analyze the long-term impact of skill-obsolescence, workers are grouped into two age groups, which are additionally differentiated by the education level defining four worker-group cells. On the other hand, the current chapter uses the educational grouping of workers only as a control, and the age categorization is not interacted with the educational composition resulting in four age and one educational groups.

[130] Manufacturing includes the following sectors (NACE2 classification): 10-44, while services include sectors 45-99.

[131] Another reason for splitting the database into manufacturing and services samples has to do with the more precise measurement of capital in manufacturing. Note, however, that as discussed by Ours and Stoeldraijer (2011) or Dostie (2011), the omission of the exact capital stock does not largely affect the production function estimates since the corresponding productivity effects tend to be small.

be overrepresented in less productive manufacturing firms, while in the services sector they tend to be employed in more productive firms. The productivity advantage of the youngest worker group in the manufacturing sector is present also in the LD specification, though it is less pronounced than using FE.[132] The pattern of larger productivity advantages for the youngest workers in the manufacturing sample (in comparison with the services sample) holds also in the final set of LP+FE and ACF+FE estimations. As expected, the LP+FE results are quantitatively similar to the FE estimates, and suggest a drop of productivity at the ages of 35, 45 and 55 in the manufacturing sample, while in the services productivity drops only at the ages of 45 and 55. ACF+FE estimates imply a drop of productivity at the age of 35 in the manufacturing sample[133], and at the ages of 45 and 55 in the services.

Thus, in sum, the robustness checks reveal some heterogeneity in the firms' age – productivity profiles. As shown by the separate estimates on manufacturing and services samples, the youngest have larger productivity advantage in the manufacturing sample, and productivity starts to decrease at later ages in the services firms. Additionally, the separate estimates by period reveal that most of the productivity disadvantage of the older workers disappears after 2000: FE estimates show a minor productivity advantage for the youngest worker group, and a flat age – productivity profile afterwards; however, methods taking care of both firm fixed effects and simultaneity imply an essentially flat age – productivity profile

[132] On the basis of the second set of robustness checks analyzing the 1992-2000 and 2001-2008 periods separately, one would rightly argue that sector estimates may also differ across periods. However, splitting the panel into many separate samples increases data demands and makes it impossible to carry out reliable estimations via LD and ACF. However, the main conclusion from the previous paragraph that the productivity disadvantage of the oldest worker group disappears after 2000, holds here as well, and the pooled estimates are closer to the 1992-2000 period results. I carried out estimations using OLS and FE on period-sector subsamples. These are shown in the Appendix Table 3.10. In the first period the FE estimates by sector are almost identical after the age of 35, while for workers below 35 the advantage is larger in the manufacturing sample. In the second period, the productivity disadvantage of the oldest group (relative to the reference group) disappears in both sectors, and the below 35 worker group is estimated to be significantly more productive than the reference group only in the manufacturing sector.

[133] In the ACF+FE specification, the coefficient estimates on the productivity of "workers 45-55" and "over 55" (relative to 35-45) are negative and show a decreasing pattern, but they are statistically not significant.

for the period 2001-2008. Therefore, managers' concerns about the lower productivity of older employees is not supported by the data after 2000.

As the question of employability also relates to the question of how older workers are compensated for their work, as a final extension, I discuss briefly how the productivity contribution of the various age groups compares to their contribution to firm-level wage costs, i.e. I compare age – productivity and age – wage profiles. This analysis originates from Hellerstein and Neumark (1999), and was subsequently applied later, e.g. by Van Biesebroeck (2007), Dostie (2011), Ours and Stoeldraijer (2011), Cataldi et al (2011), etc. Note, however, that the aim of the current analysis is not to give a rigorous comparison of relative marginal productivities and relative wages of various worker groups as was originally done by Hellerstein and Neumark (1999). The somewhat less ambitious aim is to see how the productivity contribution of the various age groups relates to their contribution to the firm-level wage costs. I apply the version proposed by Ours and Stoeldraijer (2011) and used also by Cataldi et al (2011) and Vandenberghe et al (2012). Besides regressing value added on capital, labor and the worker composition variables, a firm-level wage equation is estimated using the same regressors but the firm-level wage cost as the dependent variable[134]. Thus, while the production function estimates give information about how the various worker groups contribute to productivity, the age share coefficients from the wage equation tell us about the contribution of worker groups to the wage costs. Comparing the two coefficients reveals if wage changes associated with ageing are larger or smaller than productivity changes[135]. Ours

[134] Following Hellerstein and Neumark (1999), the firm-level wage equation can be considered a definitional equation, aggregating individual-level equations over all workers. For more detailed discussion of the firm-level wage equation, see for example, Hellerstein, Neumark (1999), page 100. The firm-level wage cost applied in the current analysis comes from the aggregation of individual wages at the firm.

[135] Note that while comparing the age share coefficients from the production function and wage equation may be also interpreted as a test of the equality of the relative marginal products and relative wages of the various worker groups, it involves several simplifying assumptions. Therefore, I avoid interpreting the test in this way.

and Stoeldraijer (2011) proposes[136] to compare the productivity and wage cost coefficients directly by regressing the wage – productivity gap (gap = ln wage – ln value added) on the same regressors as used in the previous analyzes. Table 3.7 summarizes the wage equation and the wage – productivity gap equation estimates in comparison with the production function results. Based on the previous analysis showing that production function estimates are rather different in the two periods before and after 2000, the cost function and the gap estimations are carried out separately for the two periods[137]. The FE cost function estimates in the first period imply somewhat smaller wages for workers aged 45-55, which is in line with the productivity disadvantage of this worker group. On the other hand, in case of the youngest worker group, productivity advantages outweigh the associated costs, while the opposite is true for the oldest worker group. In the second period, the age – wage cost profile is slightly increasing, and with the exception of the youngest worker group, productivity contributions are in line with wage cost contributions. For workers below 35, the productivity advantages outweigh the wage costs. Thus, the analysis of comparing wage and productivity contributions confirms the previous conclusion regarding the employability of older employees. On average, the data did not support evidence of decreasing productivity with age in the period after 2000, and older workers are paid according to their relative contribution to output.

[136] And subsequently used by Cataldi et al (2011), Vandenberghe et al (2012).
[137] Based on the previous analysis, the magnitudes of the FE and LP+FE estimates are very similar. Thus, I report only the FE estimates besides OLS. I also experimented with ACF's specification, but it implied essentially flat age – wage cost profiles in both periods, estimates were insignificant with large standard errors.

3.6 Conclusion

The paper analyzes the age – productivity profiles of Hungarian firms using linked employer-employee data from 1992-2008. Learning more about the relationship between age and productivity is an important element of labor market policy programs, which aim to improve the employability of older employees.

The results on the pooled sample covering the years of 1992-2008 are suggestive that older workers are less productive. Estimates obtained via FE, LP+FE and ACF+FE all document that productivity drops significantly at the ages of 35, 45 and 55: the coefficient estimate on the productivity of workers below 35 (relative to workers aged 35-45) is around 0.6 – 0.7; the estimates for those employees aged 45-55 lie in the range of -0.12 – -0.1, while the estimates for workers aged over 55 are in the range of -0.2 – -0.17. Splitting the database into manufacturing and services samples leaves the basic finding of decreasing productivity – age profile unchanged, but the relative advantage of the youngest worker group (below 35) is larger in the manufacturing sample, and in the services productivity drops first at the age of 45.

However, splitting the panel into two distinct periods reveals that the productivity disadvantage of older workers disappears by the most recent years. The pattern of decreasing productivity at the ages of 35, 45 and 55 holds only in the first period after the regime change (1992-2000) when workers having pre-transitional experience also had to face with the devaluation of those skills. It was the group of the youngest workers who adapted most quickly to the new labor market skills, which is reflected by their relatively high productivity. In the period of 2001-2008, both methods handling the heterogeneity and the simultaneity issues (LP+FE and ACF+FE) imply essentially flat age – productivity profiles. Similar age –

productivity profiles are documented in several other countries, e.g. by Göbel and Zwick (2009) in Germany, by Ours and Stoeldraijer (2011) in the Netherlands or by Cardoso et al (2011) in Portugal. The comparison of age – productivity and age – wage profiles also suggests positive outcome regarding the employability of older employees: wage rewards are in line with productivity contributions. Thus, the results presented in the current chapter do not confirm the negative impact of the aging population on firms' productivity and profitability. Though in the first period after the regime change older workers' productivity lagged behind the productivity of younger employees, their productivity disadvantage disappeared after 2000. The results support that policies aiming to increase the employment of older employees, e.g. by postponing the retirement age, are not likely to have an adverse impact on firms' productivity.

3.7 References

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3.8 Tables and Figures

Figure 3.1: Age – productivity profiles in the baseline model with four age groups, Cross-sectional methods
The corresponding results are shown by Table 3.3.

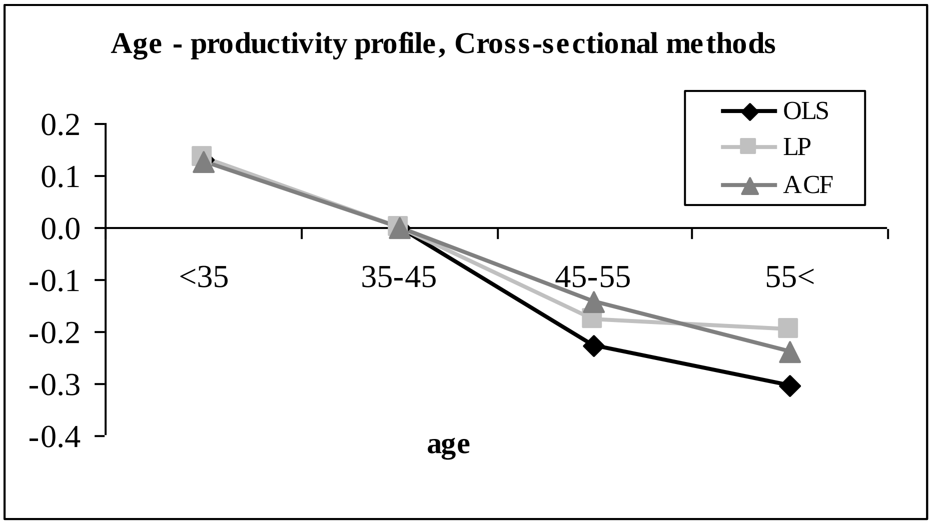

Figure 3.2: Age – productivity profiles in the baseline model with four age groups, Within methods I.
The corresponding results are shown by Table 3.3.

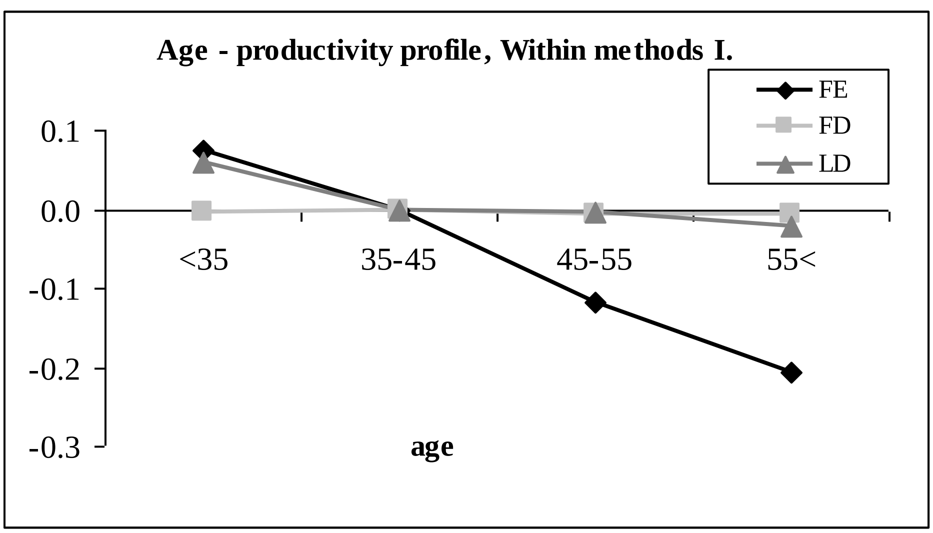

Figure 3.3: Age – productivity profiles in the baseline model with four age groups, Within methods II.
The corresponding results are shown by Table 3.3.

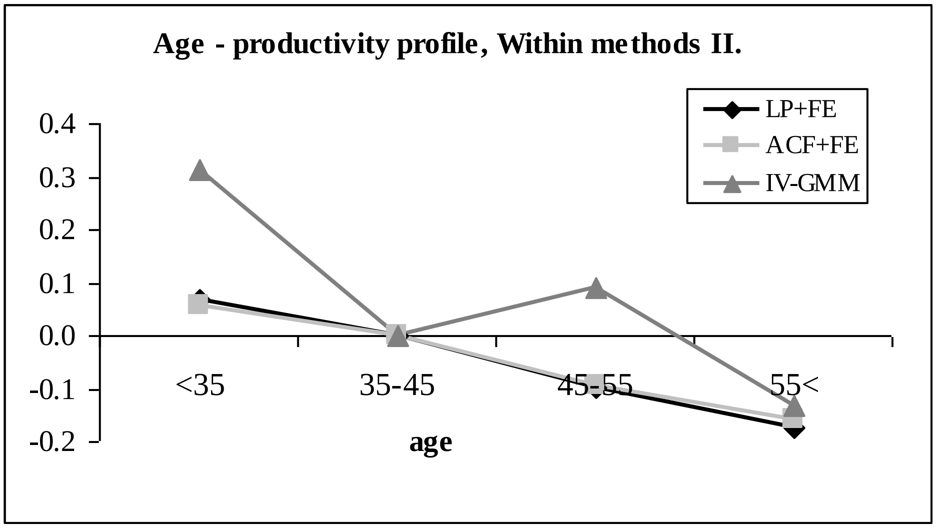

Figure 3.4: Age – productivity profiles using 5-year age categories (eight age groups)
The corresponding results are shown by Table 3.4.

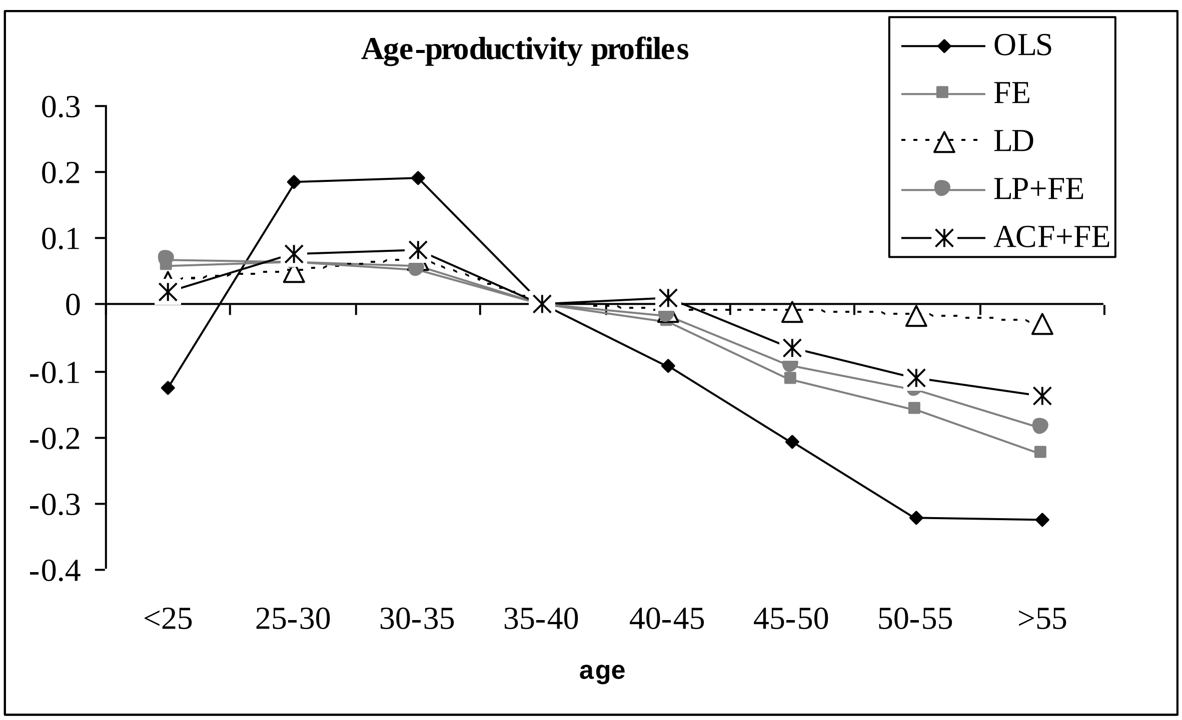

Table 3.1: Descriptive statistics of traditional firm- level input and output variables

		Mean	Standard Dev.	Min	Max	Obs
log value added	level	12.395	1.837	1.792	20.801	91,642
	mean-diff	0.000	0.485	-7.056	4.807	91,642
	first-diff	0.052	0.463	-5.974	6.810	53,632
	long-diff	0.215	0.651	-6.683	6.153	31,479
log capital	level	11.364	2.198	0.023	20.486	91,642
	mean-diff	0.000	0.533	-7.825	4.814	91,642
	first-diff	0.044	0.364	-3.912	6.805	53,632
	long-diff	0.253	0.676	-6.889	7.793	31,479
log employment	level	4.101	1.433	1.609	11.522	91,642
	mean-diff	0.000	0.318	-4.664	3.203	91,642
	first-diff	-0.038	0.221	-3.734	2.919	53,632
	long-diff	-0.098	0.425	-4.571	5.523	31,479
log material costs	level	11.714	1.961	1.099	20.906	91,642
	mean-diff	0.000	0.536	-6.036	4.970	91,642
	first-diff	0.091	0.398	-6.372	4.934	53,632
	long-diff	0.332	0.640	-5.245	6.905	31,479

Table 3.2: Descriptive statistics of the worker composition variables

		Mean	Standard Dev.	Min	Max	Obs	% if zero observations
age 18-35	level	0.356	0.228	0	1	91,642	8.2%
	mean-diff	0.000	0.107	-0.700	0.810	91,642	13.8%
	first-diff	-0.012	0.131	-1	1	53,632	7.3%
	long-diff	-0.030	0.168	-1	1	31,479	3.7%
age 35-45	level	0.274	0.168	0	1	91,642	8.8%
	mean-diff	0.000	0.108	-0.667	0.799	91,642	13.8%
	first-diff	-0.004	0.130	-1	1	53,632	6.3%
	long-diff	-0.020	0.175	-1	1	31,479	2.3%
age 45-55	level	0.284	0.186	0	1	91,642	10.5%
	mean-diff	0.000	0.109	-0.629	0.796	91,642	14.8%
	first-diff	0.007	0.129	-1	1	53,632	7.2%
	long-diff	0.021	0.178	-1	0.947	31,479	2.7%
age over 55	level	0.087	0.122	0	1	91,642	45.9%
	mean-diff	0.000	0.076	-0.533	0.880	91,642	28.1%
	first-diff	0.010	0.086	-1	1	53,632	36.0%
	long-diff	0.029	0.117	-1	1	31,479	27.1%
female	level	0.380	0.288	0	1	91,642	9.6%
	mean-diff	0.000	0.109	-0.924	0.917	91,642	16.6%
	first-diff	0.001	0.156	-1	1	53,632	11.1%
	long-diff	-0.002	0.169	-1	1	31,479	6.6%
degree	level	0.126	0.183	0	1	91,642	37.9%
	mean-diff	0.000	0.065	-0.775	0.867	91,642	29.0%
	first-diff	0.003	0.083	-1	1	53,632	32.2%
	long-diff	0.008	0.097	-0.900	1	31,479	26.1%

Table 3.3: Production function estimates, Baseline model

	Cross-sectional			Within methods I.			Within methods II.		
	OLS	**LP**	**ACF**	**FE**	**FD**	**LD**	**LP+FE**	**ACF+FE**	**IV-GMM**
log capital	0.225	0.356	0.274	0.109	0.0963	0.0702	0.201	0.156	0.275
	*0.00463****	*0.0192*	*0.0242****	*0.00706****	*0.0104****	*0.0119****	*0.013*	*0.0151****	*0.165**
log employment	0.802	0.552	0.760	0.690	0.559	0.711	0.562	0.705	0.689
	*0.00751****	*0.00945****	*0.0101****	*0.0133****	*0.0192****	*0.0224****	*0.0158****	*0.0057****	*0.147****
female	-0.0816	0.136	-0.022	-0.00512	-0.00252	0.0549	0.0132	-0.077	-0.029
	*0.0238****	*0.0232****	*0.0375*	*0.0197*	*0.0105*	*0.0211****	*0.0194*	*0.0200****	*0.462*
degree	1.705	1.367	1.701	0.344	0.0214	0.104	0.304	0.418	2.289
	*0.0392****	*0.0366****	*0.0474****	*0.0403****	*0.0215*	*0.0356****	*0.0398****	*0.0205****	*1.121***
younger than 35	0.130	0.133	0.128	0.074	-0.004	0.058	0.068	0.062	0.313
	*0.0297****	*0.0282****	*0.0595***	*0.0221****	*0.0139*	*0.0231***	*0.0217****	*0.0301***	*0.294*
aged 45-55	-0.227	-0.177	-0.141	-0.118	-0.00678	-0.00461	-0.0989	-0.099	0.090
	*0.0315****	*0.0298****	*0.0521****	*0.0218****	*0.0143*	*0.0225*	*0.0214****	*0.0269****	*0.246*
aged over 55	-0.304	-0.195	-0.237	-0.206	-0.00719	-0.0206	-0.174	-0.168	-0.131
	*0.0474****	*0.0446****	*0.0692****	*0.0349****	*0.0238*	*0.0309*	*0.0345****	*0.0353****	*0.380*
Obs	91,642	91,642	54,856	91,642	34,878	15,299	91,642	54,856	11,682
Hansen-J test									0.398
Under-identification									0.601
Weak idenitification									0.696
Endogeneity									0.403

Standard errors in Italic, stars indicate significance levels: *p<0.1, **p<0.05, ***p<0.01. Standard errors are robust to firm-level clustering. All specifications include controls for industry-year interactions, region and ownership. Reference categories: proportion male, proportion of workers without degree, proportion of workers aged 35-45. Regressions using the Ackerberg, Caves, Frazer (2006) method use the following orthogonality conditions: the innovation in productivity is orthogonal to the current values of the endogenous variables (capital, labor and worker shares). In the IV-GMM specification, the equation is estimated in first differences using the lagged 3-6 values of the endogenous variables as instruments. The reported statistics include p-values for Hansen-J statistic (null hypothesis is that instruments are valid), p-value for the Kleibergen-Paap rk LM statistic (null hypothesis is that the equation is under-identified), p-value for the Kleibergen-Paap rk Wald statistic (null corresponds to weak instruments), and a difference of Hansen statistics (C test) to test the endogeneity of the variables (null corresponds to exogeneity).

Table 3.4: Production function estimates using 5-year age intervals

	OLS	FE	LD	LP+FE	ACF+FE
log capital	0.224	0.109	0.0702	0.192	0.166
	*0.00463****	*0.00706****	*0.0119****	*0.008*	*0.018****
log employment	0.803	0.690	0.711	0.562	0.710
	*0.00752****	*0.0133****	*0.0224****	*0.0158****	*0.006****
female	-0.0725	-0.00484	0.0551	0.0133	
	*0.0237****	*0.0197*	*0.0211****	*0.0194*	
degree	1.676	0.343	0.103	0.305	
	*0.0394****	*0.0404****	*0.0356****	*0.0399****	
younger than 25	-0.126	0.0583	0.0332	0.0668	0.018
	*0.0452****	*0.0325**	*0.0336*	*0.0317***	*0.054*
aged 25-30	0.184	0.0655	0.0490	0.0640	0.077
	*0.0450****	*0.0321***	*0.0318*	*0.0315***	*0.060*
aged 30-35	0.192	0.0581	0.0679	0.0513	0.084
	*0.0427****	*0.0286***	*0.0288***	*0.0281**	*0.065*
aged 35-40			ref		
aged 40-45	-0.0916	-0.0269	-0.0104	-0.0160	0.012
	*0.0401***	*0.0265*	*0.0271*	*0.0259*	*0.048*
aged 45-50	-0.207	-0.113	-0.0119	-0.0908	-0.065
	*0.0423****	*0.0305****	*0.0320*	*0.0298****	*0.059*
aged 50-55	-0.321	-0.160	-0.0154	-0.129	-0.111
	*0.0436****	*0.0315****	*0.0313*	*0.0310****	*0.062**
over 55	-0.326	-0.226	-0.0292	-0.187	-0.138
	*0.0513****	*0.0390****	*0.0347*	*0.0385****	*0.067***
Obs	91,642	91,642	15,299	91,642	54,856

Standard errors in italic, stars indicate significance levels: *p<0.1, **p<0.05, ***p<0.01. Standard errors are robust to firm-level clustering. All specifications include controls for industry-year interactions, region and ownership. Reference categories: proportion male, proportion of workers without degree, proportion of workers aged 35-40. Regressions using the Ackerberg, Caves, Frazer (2006) method apply the following orthogonality conditions: the innovation in productivity is orthogonal to the current values of the endogenous variables (capital, labor and worker shares). Note that the ACF+FE specification does not include gender and educational composition controls due to the much larger number of parameters, which makes the optimization procedure complicated and imprecise. For more details, see Footnote 124 in the main text.

Table 3.5: Production function estimates separately for two periods, 1992-2000 and 2001-2008

	OLS		**FE**		**LD**		**LP+FE**		**ACF+FE**	
	1992-2000	**2001-2008**	**1992-2000**	**2001-2008**	**1992-2000**	**2001-2008**	**1992-2000**	**2001-2008**	**1992-2000**	**2001-2008**
log capital	0.202	0.236	0.105	0.0838	0.0838	0.0460	0.205	0.169	0.201	0.109
	*0.00630****	*0.00540****	*0.0122****	*0.00853****	*0.0186****	*0.0326*	*0.011*	*0.012*	*0.037****	*0.010****
log employment	0.799	0.806	0.749	0.631	0.763	0.646	0.587	0.540	0.734	0.676
	*0.00992****	*0.00885****	*0.0182****	*0.0169****	*0.0380****	*0.0519****	*0.0236****	*0.0189****	*0.012****	*0.024****
female	-0.0164	-0.116	-0.0392	0.0525	0.0705	0.0704	-0.0207	0.0577	-0.226	0.004
	0.0302	*0.0292****	*0.0212**	*0.0279**	*0.0300***	*0.0481*	*0.0205*	*0.0277***	*0.037****	*0.018*
degree	1.855	1.643	0.203	0.143	0.0304	0.00205	0.191	0.139	0.306	0.277
	*0.0593****	*0.0437****	*0.0664****	*0.0371****	*0.0686*	*0.0612*	*0.0633****	*0.0367****	*0.041****	*0.282*
younger than 35	0.204	0.0915	0.0530	0.0447	0.0251	0.0686	0.0484	0.0425	-0.010	0.050
	*0.0401****	*0.0394***	*0.0292**	*0.0265**	*0.0415*	*0.0421*	*0.0284**	*0.0260*	*0.050*	*0.046*
aged 45-55	-0.235	-0.218	-0.0865	-0.0253	0.00545	0.0490	-0.0693	-0.0235	-0.058	-0.020
	*0.0425****	*0.0434****	*0.0285****	*0.0272*	*0.0364*	*0.0441*	*0.0277***	*0.0269*	*0.057*	*0.140*
aged over 55	-0.304	-0.295	-0.213	-0.0297	-0.0204	0.0276	-0.184	-0.0298	-0.166	-0.020
	*0.0739****	*0.0573****	*0.0529****	*0.0388*	*0.0583*	*0.0555*	*0.0513****	*0.0384*	*0.074***	*0.126*
Obs	38,198	53,444	38,198	53,444	3,609	2,961	38,198	53,444	22,349	28,375

Standard errors in italic, stars indicate significance levels: *p<0.1, **p<0.05, ***p<0.01. Standard errors are robust to firm-level clustering. All specifications include controls for industry-year interactions, region and ownership. Reference categories: proportion male, proportion of workers without degree, proportion of workers aged 35-45. Regressions using the Ackerberg, Caves, Frazer (2006) method apply the following orthogonality conditions: the innovation in productivity is orthogonal to the current values of the endogenous variables (capital, labor and worker shares).

Table 3.6: Production function estimates on separate manufacturing and services samples

	OLS		FE		LD		LP+FE		ACF+FE	
	manufacturing	**services**	**manufacturing**	**services**	**manufacturing**	**services**	**manufacturing**	**services**	**manufacturing**	**services**
log capital	0.233	0.223	0.0998	0.104	0.0599	0.0650	0.222	0.192	0.187	0.125
	*0.00851****	*0.00564****	*0.0121****	*0.00896****	*0.0172****	*0.0173****	*0.017*	*0.011*	*0.032****	*0.019****
log employment	0.774	0.825	0.688	0.693	0.692	0.734	0.548	0.570	0.675	0.719
	*0.0132****	*0.00991****	*0.0198****	*0.0199****	*0.0308****	*0.0366****	*0.0236****	*0.0224****	*0.015****	*0.007****
female	-0.202	-0.0380	-0.0184	-0.00229	0.0385	0.0810	0.0162	0.00621	-0.116	-0.183
	*0.0389****	*0.0321*	*0.0302*	*0.0293*	*0.0302*	*0.0342***	*0.0291*	*0.0289*	*0.042****	*0.027****
degree	2.129	1.583	0.429	0.309	0.151	0.0752	0.388	0.268	0.621	0.352
	*0.0906****	*0.0447****	*0.0786****	*0.0481****	*0.0567****	*0.0505*	*0.0770****	*0.0471****	*0.048****	*0.032****
younger than 35	0.0789	0.167	0.160	0.0423	0.0653	0.0520	0.141	0.0480	0.165	0.029
	*0.0457**	*0.0422****	*0.0348****	*0.0312*	*0.0334**	*0.0345*	*0.0343****	*0.0304*	*0.062****	*0.049*
aged 45-55	-0.270	-0.210	-0.108	-0.129	-0.00501	-0.000994	-0.0882	-0.102	-0.053	-0.090
	*0.0472****	*0.0478****	*0.0330****	*0.0331****	*0.0294*	*0.0366*	*0.0321****	*0.0327****	*0.057*	*0.044***
aged over 55	-0.468	-0.162	-0.187	-0.199	-0.0381	-0.0199	-0.143	-0.163	-0.098	-0.128
	*0.0751****	*0.0682***	*0.0525****	*0.0525****	*0.0440*	*0.0481*	*0.0518****	*0.0515****	*0.074*	*0.060***
Obs	34,471	47,306	34,471	47,306	7,684	5,558	34,471	47,306	22,471	25,775

Standard errors in italic, stars indicate significance levels: *p<0.1, **p<0.05, ***p<0.01. Standard errors are robust to firm-level clustering. All specifications include controls for industry-year interactions, region and ownership. Reference categories: proportion male, proportion of workers without degree, proportion of workers aged 35-45. Regressions using the Ackerberg, Caves, Frazer (2006) method apply the following orthogonality conditions: the innovation in productivity is orthogonal to the current values of the endogenous variables (capital, labor and worker shares).

Table 3.7: Production function, Cost function and Gap (ln wage costs – ln value added) estimates on samples 1992-2000 and 2001-2008

	1992-2000						2001-2008					
	OLS			FE			OLS			FE		
	prod	cost	gap	prod	cost	gap	prod	cost	gap	prod	cost	gap
log capital	0.200	0.0655	-0.134	0.108	0.0348	-0.0702	0.233	0.0591	-0.175	0.0749	0.0175	-0.0579
	*0.00627****	*0.00392****	*0.00623****	*0.0123****	*0.00939****	*0.0142****	*0.00534****	*0.00256****	*0.00503****	*0.00824****	*0.00597****	*0.00940****
log employment	0.803	0.874	0.0706	0.767	0.831	0.0667	0.808	1.000	0.194	0.648	0.881	0.231
	*0.00987****	*0.00633****	*0.0102****	*0.0185****	*0.0173****	*0.0229****	*0.00879****	*0.00435****	*0.00829****	*0.0170****	*0.0142****	*0.0200****
female	-0.0272	-0.148	-0.124	-0.0900	-0.0769	0.0136	-0.113	-0.190	-0.0808	0.0513	-0.144	-0.181
	0.0289	*0.0172****	*0.0288****	*0.0197****	*0.0174****	*0.0245*	*0.0291****	*0.0148****	*0.0286****	*0.0284**	*0.0331****	*0.0430****
degree	1.852	1.202	-0.645	0.196	0.562	0.373	1.646	1.162	-0.471	0.159	0.374	0.218
	*0.0594****	*0.0373****	*0.0614****	*0.0679****	*0.0557****	*0.0776****	*0.0437****	*0.0235****	*0.0420****	*0.0374****	*0.0421****	*0.0551****
younger than 35	0.200	-0.166	-0.363	0.0623	-0.0373	-0.0969	0.0982	-0.0732	-0.174	0.0634	0.00238	-0.0704
	*0.0400****	*0.0253****	*0.0412****	*0.0296***	*0.0296*	*0.0388***	*0.0393***	*0.0235****	*0.0396****	*0.0267***	*0.0269*	*0.0365**
aged 45-55	-0.227	0.111	0.333	-0.0855	-0.0549	0.0414	-0.208	0.0648	0.269	-0.0221	0.0102	0.0216
	*0.0426****	*0.0281****	*0.0445****	*0.0291****	*0.0304**	*0.0394*	*0.0434****	*0.0257***	*0.0434****	*0.0276*	*0.0282*	*0.0375*
aged over 55	-0.294	0.236	0.521	-0.194	-0.0165	0.176	-0.274	0.238	0.511	-0.0184	0.0625	0.0744
	*0.0736****	*0.0462****	*0.0757****	*0.0535****	*0.0538*	*0.0713***	*0.0570****	*0.0321****	*0.0558****	*0.0394*	*0.0361**	*0.0508*
Obs	38,198	38,580	38,132	38,198	38,580	38,132	53,444	54,874	53,444	53,444	54,874	53,444

Standard errors in italic, stars indicate significance levels: *p<0.1, **p<0.05, ***p<0.01. Standard errors are robust to firm-level clustering. All specifications include controls for industry-year interactions, region and ownership. Reference categories: proportion male, proportion of workers without degree, proportion of workers aged 35-45. Regressions using the Ackerberg, Caves, Frazer (2006) method apply the following orthogonality conditions: the innovation in productivity is orthogonal to the current values of the endogenous variables (capital, labor and worker shares).

3.9 Appendix

Simultaneity and the structural methods (Levinsohn and Petrin 2003, Ackerberg, Caves and Frazer 2006)

In the final specifications I apply methods that take a structural approach to handle the simultaneity issue. Authors of this literature (Olley and Pakes, 1996, henceforth OP; Levinsohn and Petrin, 2003, henceforth LP; Ackerberg, Caves and Frazer, 2006, henceforth ACF) suggest controlling for the unobserved productivity term ω_{jt} by using the observed input decisions of the firm. OP proposes using the investment decision of the firm to proxy the unobserved productivity, while LP and ACF apply intermediate inputs (e.g. material costs, energy) to control for the missing component.

LP suggests a two-stage procedure, in which the labor coefficient is identified in the first stage, while the capital coefficient is obtained in the second step. To proxy the unobserved productivity, LP use the intermediate demand function of the firm: $int\_goods_{jt} = f(\omega_{jt}, k_{jt})$. Assuming that the intermediate inputs are strictly increasing function of ω_{jt}, the demand function can be inverted to obtain a proxy for the unobserved productivity. Using material costs as intermediate inputs, the unobserved productivity is taken into account in the production function by a nonparametric function of material costs and capital $\omega_{jt} = g(\ln K_{jt}, \ln M_{jt})$. Plugging the inverse material demand function into the production function gives the first stage equation:

$$\ln VA_{jt} = \beta_2 \cdot \ln L_{jt} + \sum_k \gamma_k \cdot l_{k_{jt}} + \lambda \cdot X + \Psi(\ln K_{jt}, \ln M_{jt}) + \varepsilon_{jt} \qquad (1)$$

The term $\Psi(\ln K_{jt}, \ln M_{jt}) = \beta_0 + \beta_1 \cdot \ln K_{jt} + g(\ln K_{jt}, \ln M_{jt})$ includes the $g(.)$ proxy function and the capital term of the production function as it cannot be identified separately due to collinearity issues. I estimate equation (1) approximating $\psi(.)$ by third order polynomials:

$$\ln VA_{jt} = \beta_0 + \beta_2 \cdot \ln L_{jt} + \sum_k \gamma_k \cdot l_k + \lambda \cdot X + \sum_{p=0}^{3} \sum_{q=0}^{3-p} \delta_{pq} \cdot (\ln K_{jt})^p (\ln M_{jt})^q + \varepsilon_{jt} \quad (2)$$

Equation (2) can be estimated by OLS to obtain consistent estimates of the labor input and the worker share coefficients.

Note that in the first stage one obtains an estimate of the labor input and the worker shares, as well as the composite term $\hat{\Psi}_{jt}$. The second stage regression is then constructed as follows. First, assume that productivity follows a first order Markov process:

$$\omega_{jt} = E[\omega_{jt} \mid I_{jt-1}] + \xi_{jt} = E[\omega_{jt} \mid \omega_{jt-1}] + \xi_{jt} = g(\omega_{jt-1}) + \xi_{jt}. \quad (3)$$

Second, note the timing assumptions. Time t capital is decided at time t – 1, thus, it is uncorrelated with the innovation in productivity at time t, ζ_{jt}. Labor and material costs are freely variable inputs, and are correlated with the contemporaneous innovation in productivity. Third, using the definition of the composite term, one can express the unobserved productivity as:

$$\omega_{jt} = \hat{\Psi}_{jt} - \beta_1 \cdot \ln K_{jt}. \quad (4)$$

The capital coefficient is then obtained in the following way. Pick a candidate value of the capital coefficient β_1^0. Construct $\omega_{jt} = \hat{\Psi}_{jt} - \beta_1^0 \cdot \ln K_{jt}$ for each j and t. Regress non-parametrically ω_{jt} on ω_{jt-1} and obtain the residuals ξ_{jt}. Compute the moment interacting the contemporaneous capital and residual and continue the procedure by choosing new values of the capital coefficient until the moment is minimized[138].

The linearity of the first stage equation (2) offers the opportunity to include firm fixed effects into LP's model when estimating the labor and the worker share coefficients. I remove firm fixed effects at this stage by time demeaning the variables in equation (2) [139].

ACF questions the validity of the first stage regression of the LP procedure noting that neither the capital nor the labor coefficients may be identified in the first stage due to collinearity issues. As labor and material costs are both perfectly variable inputs in the LP model and chosen simultaneously, they are probably allocated in a similar way. Thus, labor is likely to be determined by the same state variable ω_{jt} as the intermediate input, therefore, it

[138] Alternatively, the capital coefficient can be estimated from the following second-stage equation:

$$\ln VA_{jt} - \hat{\beta}_2 \cdot \ln L_{jt} - \sum_k \hat{\gamma}_k \cdot l_k = \beta_0 + \beta_1 \cdot \ln K_{jt} + g(\hat{\Psi}_{jt} - \beta_1 \cdot \ln K_{jt}) + \xi_{jt} + \varepsilon_{jt}.$$

In the above equation, none of the right-hand side variables are correlated with the error term $\xi_{jt} + \varepsilon_{jt}$, hence, the capital coefficient can be estimated consistently via non-linear least squares.

[139] The first stage equation is linear in the labor, in the worker share variables, and in the polynomial terms (capital – labor interaction terms). Thus, demeaning all these variables, one can obtain an estimate of the labor and worker share coefficients in the first stage taking into account both the simultaneity and the selection issue. The $\hat{\delta}$ coefficient estimates of the polynomial terms are not important at this stage.

does not vary independently from the $g(.)$ proxy function. As a consequence, neither the labor nor the share coefficients can be identified in the first stage. ACF suggests netting out only the noise parameter in the first step, and identifying all input coefficients in the second stage.

The timing assumptions are crucial for deriving the moment conditions. One possibility is that capital is decided at period $t-1$, labor (and the quality of labor, hence, worker shares) is chosen at $t-b$ ($0 < b < 1$), and the intermediate input is determined at time t. The productivity is assumed to follow a first order Markov process between $t-1$, $t-b$ and t. Due to the timing assumption, the demand for material costs is also a function of labor and the worker share variables:

$$\ln M_{jt} = g(\omega_{jt}, \ln K_{jt}, \ln L_{jt}, l_1, \ldots, l_k, \ldots)$$

Assuming that material costs are strictly increasing in productivity, this function can be inverted, thus, unobserved productivity is proxied with a function of all inputs. The first stage equation becomes:

$$\ln VA_{jt} = \Psi(\ln K_{jt}, \ln M_{jt}, \ln L_{jt}, l_1, \ldots, l_k, \ldots) + \varepsilon_{jt} \quad (5)$$

$$\Psi(\ln K_{jt}, \ln M_{jt}, \ln L_{jt}, l_1, \ldots, l_k, \ldots) = \beta_0 + \beta_1 \cdot \ln K_{jt} + \beta_2 \cdot \ln L_{jt} + \sum_k \gamma_k \cdot l_k + \omega_{jt}$$

Equation (5) is estimated by using a third-order polynomial approximation of the $\psi(.)$ function.

The aim of the first stage is to separate the error term from the unobserved productivity and to obtain predicted values of $\hat{\Psi}_{jt}$. These predicted values will be used in the second stage to model the unobserved productivity. The steps of the second stage are similar to LP. Using the assumption that productivity follows a first order Markov process, it can be written as follows:

$$\omega_{jt} = E\lfloor \omega_{jt} \mid I_{jt-1} \rfloor + \xi_{jt} = E\lfloor \omega_{jt} \mid \omega_{jt-1} \rfloor + \xi_{jt} = g(\omega_{jt-1}) + \xi_{jt} \quad (6)$$

In the above expression ζ_{jt} represents the innovation in productivity. Due to the timing assumptions, the innovation in productivity is uncorrelated with capital in period t and with the labor input and the worker shares from period $t-1$. Consequently, the identifying moment conditions are as follows:

$$E\left[\xi_{jt} \mid \begin{array}{c} \ln K_{jt} \\ \ln L_{jt-1} \\ l_{jt-1}^{1} \\ \vdots \\ l_{jt-1}^{k} \end{array}\right] = 0 \qquad (7)$$

As ACF notes, the researcher may alternatively assume that the labor inputs were chosen at or prior to $t - 1$.[140] Hence, an alternative set of identifying moment conditions are:

$$E\left[\xi_{jt} \mid \begin{array}{c} \ln K_{jt} \\ \ln L_{jt} \\ l_{jt}^{1} \\ \vdots \\ l_{jt}^{k} \end{array}\right] = 0 \qquad (8)$$

In practice, the procedure is carried out as follows. Obtain predicted $\hat{\Psi}_{jt}$ in the first step. Pick an initial value of the parameters, and construct

$$\omega_{jt} = \hat{\Psi}_{jt} - \beta_1^0 \cdot \ln K_{jt} - \beta_2^0 \cdot \ln L_{jt} - \sum_k \gamma_k^0 \cdot l_k . \qquad (9)$$

Then, I apply the formula in (6) by using fourth-degree polynomial approximation. The aim of the regression is to obtain the residuals, the ζ_{jt} innovation in productivity and compute the sample analogue of the moment conditions. The procedure is repeated until the sample moment conditions are minimized.

Including firm fixed effects into the ACF model requires netting out not only the noise term, but also firm fixed effects in the first-stage equation. Thus, I estimate equation (5) via the fixed effect estimator[141], and obtain predicted values of $\hat{\Psi}_{jt}$, which do not include firm fixed effects. From here on, the procedure is analogous to the case without firm fixed effects[142].

Unfortunately, the ACF estimates are very sensitive to both the sample size and the number of parameters to be estimated. The precision and the reliability of the estimates decreases steadily as we estimate more and more parameters (= define less aggregated worker

[140] Konings and Vanormelingen (2010) in their paper assessing the impact of training on productivity and wages uses moment conditions with timing assumptions similar to (16). They assume that material input is chosen after labor input and training "which seems plausible for an economy with rigid labor markets like Belgium".
[141] Alternatively, one can also use first-differencing.
[142] For more information on the FE+ACF method, see Vandenberghe, Waltenberg and Rigo (2012).

groups), or as we split the sample into smaller and smaller subsamples. This is especially the case when using the lagged values as instruments defined by the moment conditions in (7) [143]. Thus, in case of the ACF estimates, I use the moment conditions described by (8).

[143] This finding is consistent with ACF (2006) noting that using the current values as instruments for identification probably yields more efficient estimates than using the lagged values, as the current inputs are more directly linked to the current output. ACF (2006) providing production function estimates on Chilean data in a two-input framework (capital and labor) also finds that standard errors are generally higher when using the lagged values of inputs as instruments.

Table 3.8: AR(1) estimates

	OLS	FE
Value added		
lnVA (t-1)	0.986	0.582
	0.00153	*0.0116*
Capital		
lnK (t-1)	0.989	0.794
	0.00117	*0.00729*
Labor		
lnL (t-1)	0.994	0.837
	0.000816	*0.00681*
younger than 35		
Y35 (t-1)	0.811	0.344
	0.00314	*0.0083*
aged 35-45		
M35 (t-1)	0.669	0.389
	0.0046	*0.00828*
aged 45-55		
M45 (t-1)	0.755	0.427
	0.00358	*0.00805*
over 55		
O55 (t-1)	0.766	0.407
	0.00626	*0.0113*
Obs	54,014	

Standard errors in Italic. Year dummies included in all regressions.

Table 3.9: Reduced form regressions

First differences: regressions of Δx_t on x_{t-2}, x_{t-3}, …, x_{t-6}
Levels: regressions of x_t on Δx_{t-2}, Δx_{t-3}, …, Δx_{t-5}

	First differences	**Levels**
Value added		
Wald	0.000	0.000
R square	0.019	0.163
Capital		
Wald	0.000	0.000
R square	0.013	0.079
Labor		
Wald	0.000	0.000
R square	0.024	0.093
younger than 35		
Wald	0.000	0.000
R square	0.024	0.094
aged 35-45		
Wald	0.000	0.000
R square	0.049	0.214
aged 45-55		
Wald	0.000	0.000
R square	0.046	0.229
over 55		
Wald	0.000	0.000
R square	0.023	0.338

Table 3.10: Production function estimates on industry-period subsamples

	OLS				FE			
	Manufacturing		Services		Manufacturing		Services	
	1992-2000	2001-2008	1992-2000	2001-2008	1992-2000	2001-2008	1992-2000	2001-2008
log capital	0.216	0.243	0.197	0.232	0.101	0.0917	0.100	0.0742
	*0.0106****	*0.0102****	*0.00827****	*0.00644****	*0.0218****	*0.0157****	*0.0151****	*0.0103****
log employment	0.771	0.776	0.815	0.834	0.713	0.658	0.784	0.610
	*0.0166****	*0.0156****	*0.0137****	*0.0114****	*0.0295****	*0.0268****	*0.0260****	*0.0225****
female	-0.132	-0.250	0.0594	-0.0781	-0.0767	0.0706	-0.0410	0.0588
	*0.0468****	*0.0501****	*0.0459*	*0.0366***	*0.0328***	*0.0454*	*0.0341*	*0.0356**
degree	2.185	2.083	1.779	1.515	0.0872	0.199	0.254	0.128
	*0.123****	*0.106****	*0.0733****	*0.0486****	*0.130*	*0.0742****	*0.0837****	*0.0421****
younger than 35	0.148	0.0192	0.262	0.134	0.127	0.0754	-0.000622	0.0274
	*0.0616***	*0.0624*	*0.0625****	*0.0520***	*0.0435****	*0.0453**	*0.0464*	*0.0325*
aged 45-55	-0.287	-0.259	-0.211	-0.207	-0.0812	-0.0426	-0.103	-0.0314
	*0.0624****	*0.0651****	*0.0719****	*0.0609****	*0.0418**	*0.0443*	*0.0468***	*0.0346*
aged over 55	-0.317	-0.520	-0.262	-0.115	-0.208	-0.0941	-0.207	-0.00408
	*0.116****	*0.0897****	*0.120***	*0.0795*	*0.0860***	*0.0628*	*0.0854***	*0.0507*
Obs	15,531	18,940	16,622	30,684	15,531	18,940	16,622	30,684

Standard errors in italic, stars indicate significance levels: *p<0.1, **p<0.05, ***p<0.01. Standard errors are robust to firm-level clustering. All specifications include controls for industry-year interactions, region and ownership. Reference categories: proportion male, proportion of workers without degree, proportion of workers aged 35-45. Regressions using the Ackerberg, Caves, Frazer (2006) method apply the following orthogonality conditions: the innovation in productivity is orthogonal to the current values of the endogenous variables (capital, labor and worker shares).