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Vintage Effects, Ageing and Productivity

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Abstract

We provide new empirical evidence on the link between age and productivity using a transitional context. Building on a model of skill obsolescence, we assess the long-term adjustment process following a sudden change in skills needed in production that severely worsened older workers' labor market situation. The model implies 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 developed in international literature and apply it to a linked employer-employee dataset from Hungary 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. The magnitude and the negative effects of the adjustment period witnessed in Hungary highlight the importance of policies aimed at providing core competencies and adult training that enable older workers to adjust to sudden economic and technological changes.

JEL classification: J14, J24, O33

Keywords: ageing, productivity, skill obsolescence

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Kor, termelékenység, és évjárat hatások

Anna Lovász - Mariann Rigó

Összefoglaló

Tanulmányunkban a vállalatok korcsoport szerinti összetétele és termelékenysége közötti kapcsolatot elemezzük tranzíciós környezetben. A humántőke modellre építve azt vizsgáljuk, hogy a transzformációs sokkot követően milyen mértékben értékelődött le a rendszerváltás előtt megszerzett munkaerőpiaci tudás, és hosszú távon hogyan alkalmazkodtak a különböző dolgozói csoportok a megváltozott munkahelyi és technológiai körülményekhez. A modell alapján (a) a humántőke leértékelődése a magasan képzett dolgozókat nagyobb mértékben érinti, (b) az idősebb korosztály hátránya idővel csökken, mivel az újabb kohorszok az új elvárásoknak megfelelő humántőkét halmoznak fel, és (c) a rendszerváltás előtt szerzett humántőke leértékelődése először a külföldi tulajdonú cégekben jelenik meg, majd pár év késéssel a hazai tulajdonú cégekben, összhangban a modern technológiák időbeli elterjedésével. A bérkülönbségek vizsgálata helyett vállalati termelési függvények alapján becsüljük az egyes (kor és iskolázottság szerinti) csoportok relatív termelékenységét. A becslést a Foglalkoztatási és Bértarifa adatbázison végezzük el, a rendszerváltás előtti időszakról (1986) majdnem húsz évvel a változások utánig (2008). Az eredmények – a modellnek megfelelően – arra utalnak, hogy az idősek és fiatalok közötti termelékenységbeli eltérés a magasan képzetteknél volt a legnagyobb (1996 és 2000 között -0,13). Az idősebbek relatív termelékenységének esése követte a modern tőke beáramlását: először a külföldi tulajdonú cégeknél volt a legnagyobb (-0,6 1992 és 1995 között), majd később a hazai magántulajdonú cégeknél jelent meg (-0,18 1996 és 2000 között), majd 2006-ra mindkettőnél eltűnt. Az eredmények alátámasztják a felnőttképzés, valamint az alapkompenciák fontosságát az idősebbek gazdasági és technológiai sokkok utáni sikeres alkalmazkodásban.

Tárgyszavak: korosodás, termelékenység, humántőke

JEL kódok: J14, J24, O33

I. 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 States¹. 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; Rigo, Vandenberghe and Waltenberg, 2011).² The results showing a decline in older workers' productivity reflect one form of skill obsolescence³: the normal wear and atrophy of 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.⁴ 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

¹ 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, Rigo, Vandenberghe and Waltenberg (2011) on Belgian data, Göbel and Zwick (2009) on German data, Hellerstein and Neumark (1999, 2004) and Haltiwanger et al (1999) on US data.

² 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.

³ 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) 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.

⁴ 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).

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 tools that can alleviate its effects: continued adult training and a focus on giving students core competencies early on that enable easier lifelong learning.⁵

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.⁶ 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 workers' productivity lasted, and

⁵ 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.

⁶ 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.

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.⁷ 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.

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

⁷ 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. 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 methodology.

group is defined in an unconventional way – above the age of 45 – as this is better suited to the transitional analysis.⁸

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 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.⁹ 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

⁸ 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.

⁹ 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.

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 methods providing within-estimates are subject to many caveats as described in the literature,¹⁰ 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.¹¹ 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.¹² 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 methods by Levinsohn and Petrin (2003) and Akerberg, Caves and Frazer (2006).

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 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

¹⁰ 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).

¹¹ 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.

¹² 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 Rigo, Vandenberghe and Waltenberg (2011) 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.

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.

II. EMPIRICAL METHODOLOGY

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,¹³ and the comprehensive analysis of Ecostat (2010) gives an overview of the labor market and macroeconomic developments from 1990 until recently. Table 1 summarizes the basic economic indicators, such as the annual changes of GDP, export, import or the CPI, and Figures 1/a and 1/b 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 workers, with a widening wage gap between skilled and unskilled labor and a decreasing returns to experience.

As illustrated by Figure 1/a, 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 1/b 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.

¹³ 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.

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 consequent 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.

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 (based on Hellerstein and Neumark, 1999). Our empirical analysis uses the following variant of the Cobb-Douglas production function:

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

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. Appendix 1 gives a more detailed overview of the model and assumptions underlying the estimated equations.

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 I_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).¹⁴ 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 regime¹⁵. 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.¹⁶ 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 .¹⁷ The underlying assumptions behind the restricted model are that the relative productivity of each group is 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.¹⁸ As our goal is to study changes in the value of skills after the transition, we relax the

¹⁴ 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 A.2.9. – A.2.12..

¹⁵ Kertesi and Köllő (2002) defines “old” as having experience more than the median years of work experience, which was 21 years.

¹⁶ 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 A.2.5. – A.2.8.

¹⁷ We control for the interaction of 19 industrial categories and year dummies, 7 regions, and ownership.

¹⁸ 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,

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.¹⁹ We refer to this specification as the *partially unrestricted model*.

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.²⁰ These estimates cannot be regarded accurate, as

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.

¹⁹ Note that our regressions results in the Appendix 2 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 4 (old skilled to young skilled, and old unskilled to young unskilled) can be simply computed from these numbers.

²⁰ 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 ownerd 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

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.

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.²¹

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.²² 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 (Levinsohn and Petrin, 2003; henceforth LP) and Akerberg, Caves and Frazer (Akerberg, Caves and

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).

²¹ 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.

²² See, for example, Aubert and Crepon (2006); Ours and Stoeldraijer (2011).

Frazer 2006, henceforth ACF).²³ 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 and ACF methods using cross-sectional data as was usually done in previous studies²⁴. Additionally, we also provide estimates taking care of both unobserved firm heterogeneity and time variant productivity shocks. This was rarely done in previous literature²⁵. Unfortunately, the ACF method often provided estimates with huge standard errors on the small subsamples divided by period and ownership²⁶. However, in order to get an idea of the possible differences between the ACF and other estimates, we computed estimates using the ACF and ACF+FE methods pooling our last two periods. The period of 2001-2008 proved to be long enough to provide reliable estimates on all subsamples by ownership type.

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

²³ Hellerstein and Neumark (2004), Dostie (2011), Vandenberghe (2011), Rigo, Vandenberghe and Waltenberg (2011) all apply structural methods to correct for biases.

²⁴ For example Hellerstein and Neumark (2004) and Dostie (2011).

²⁵ 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:

$$\ln VA_{jt} = \gamma \cdot \ln QL_{jt} + \sum_{p=0}^3 \sum_{q=0}^{3-p} \varepsilon_{pq} \cdot (\ln K_{jt})^p (\ln M_{jt})^q + \delta \cdot Z_{jt} + e_{jt}$$

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 $g(\cdot)$ 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.

Ackerberg, Caves and Frazer (2006) argues that neither capital nor the labor input coefficients can be identified in the first stage. Instead, they suggests a two-stage procedure in which the first stage serves to net out only the noise parameter, and all the input coefficients are identified in the second stage 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. Rigo, Vandenberghe and Waltenberg (2011) provides more details on the ACF+FE method estimating the impact of ageing on productivity and wages in Belgium. Appendix 1 yields further details on both structural methods.

²⁶ We found that the precision of the ACF estimates decreased as the sample size became smaller and/or as the number of parameters got larger. ACF (2006) estimated a production function with capital and labor inputs, which required estimating three parameters (capital, labor, intermediate input). However, due to our detailed worker controls, we need to estimate six parameters in the ACF model, which increases the complexity of the optimization problem.

including both firm fixed effects and the “LP term”. As a robustness check, we show ACF and FE+ACF estimates for the period 2001-2008.

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 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.

III. 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. Table 2.a. and 2.b. 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.

Table 2.c. and 2.d. 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.

IV. 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 3 and 4, while the full set of estimated coefficients are in Tables A.2.1 – A.2.12. in the Appendix.

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.²⁷ Table 3 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.²⁸ We see this confirmed in the Hungarian results, though within firms, the estimates are only significant in 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

²⁷ 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 decrease productivity. Rigo, Vandenberghe and Waltenberg (2011) 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.

²⁸ 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.

before the regime change, which increases to 1.1 – 1.3 after 1990.²⁹ 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.

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 4.30 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

²⁹ This increase is in line with the results of Kertesi and Köllő (2002) covering the years up to 1999.

³⁰ 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 2., Tables A.2.1. – A.2.12.

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.³¹

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 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

³¹ 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 Stoedraijer (2011) and Göbel and Zwick (2009). Both studies document an insignificant decrease of productivity with age in the within specification. Rigo, Vandenberghe and Waltenberg (2011) finds a small significant decrease of productivity with age.

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.

Finally, we briefly discuss the ACF estimates, obtained on the 2001-2008 sample. Table 5 depicts the full set of ACF results in comparison with all the other methods applied in the paper. Using the ACF method, the parameter estimates are very similar in magnitude to the OLS case, the difference being that the capital coefficient is somewhat higher, the labor coefficient is

slightly lower, and the skilled old – young productivity gap is a bit larger than obtained via OLS.³² The comparison of the ACF and LP estimates indicates that the labor coefficient may be downward biased in the LP case, however, the worker share estimates are less affected by the identification difficulties of the LP method as pointed out by ACF (2006).³³ The within-estimates (FE, FE+LP, FE+ACF) are even closer to each other, and we see the same pattern as in case of the cross-sectional estimates (higher capital, lower labor coefficients and slightly larger skilled old-young productivity gap in the FE+ACF specification than using only FE). In sum, the ACF and FE+ACF estimates obtained on the 2001-2008 samples indicate that the methods using the latest developments of the structural approaches as proposed by ACF (2006), produce estimates being probably very close in magnitude to our applied methods.

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.³⁴ 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.

³² This is in line with the findings of previous papers applying the ACF method. For example, Eberhardt and Helmers (2010) estimating production function with capital and labor inputs found that the ACF estimates are indeed within the OLS 95 percent confidence intervals, and their ACF labor coefficient lies somewhat below the OLS estimate. Rigo, Vandenberghe and Waltenberg (2011) also obtained ACF estimates, which are very close to the OLS results.

³³ Eberhardt and Helmers (2010) estimating production function with capital and labor input found implausibly low labor coefficient of 0.2 in the LP specification. They claim that their result 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. The labor coefficient estimated on the Hungarian data is not as unreasonably low as found by the above authors, but it is lower than expected. The coefficients on the worker share variables show smaller difference relative to the OLS case. In the within dimension, comparing the FE and FE+LP estimates, the worker share results are almost identical.

³⁴ For example, OLS estimates of production function on Belgian data (Rigo, Vandenberghe and Waltenberg, 2011) 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.

V. 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 structural methods by Levinsohn and Petrin (2003) and Akerberg, Caves and Frazer (2006), as well as using firm fixed effects specification (also with combination of the structural methods) 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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TABLES

Table 1

Basic economic indicators

<i>Year</i>	<i>GDP*</i>	<i>Industrial produc- tion*</i>	<i>Export</i>	<i>Import</i>	<i>balance of current account / GDP</i>	<i>Real earnings*</i>	<i>Employ- ment*</i>	<i>Consumer price index*</i>	<i>Unemploy- ment rate</i>
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.a

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

Table 2.b

**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-	0.311	0.285	0.224	0.062	0.465	0.250
1989	(0.096)	(0.175)	(0.137)	(0.058)	(0.140)	(0.104)
1992-	0.327	0.373	0.243	0.131	0.431	0.196
1995	(0.189)	(0.253)	(0.202)	(0.137)	(0.230)	(0.158)
1996-	0.356	0.396	0.244	0.152	0.400	0.204
2000	(0.213)	(0.280)	(0.229)	(0.153)	(0.247)	(0.176)
2001-	0.391	0.477	0.294	0.182	0.315	0.209
2005	(0.236)	(0.314)	(0.268)	(0.180)	(0.247)	(0.195)
2006-	0.389	0.502	0.323	0.179	0.288	0.210
2008	(0.246)	(0.324)	(0.284)	(0.183)	(0.246)	(0.207)

Table 2.c

**Means of firm-level variables, subsamples of foreign, domestic private,
and state-owned firms**

Period	Value added			Capital			Employment			Observations		
	Foreign	Domestic	State	Foreign	Domestic	State	Foreign	Domestic	State	Foreign	Domestic	State
1986-1989			10887			5489			682			7,620
1992-1995	6823	1630	7335	4183	966	11182	387	177	761	1,672	9,405	3,353
1996-2000	9153	1568	6778	5275	712	8978	380	135	717	4,344	17,796	2,079
2001-2005	9016	1429	4490	4860	614	6485	309	84	490	5,952	26,213	2,341
2006-2008	10585	1651	3046	4321	856	5000	303	80	329	3,865	15,547	1,525

Table 2.d

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

Period	At least 45			Educated			Educated, at least 45			Educated, below 45		
	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 3

Production function estimates, restricted model

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

Standard errors in italic, stars indicate significance levels: *p<0.05, **p<0.001, ***p<0.001. 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 4

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 <i>0.290</i>	-0.483 <i>0.0916***</i>	-0.645 <i>0.0762***</i>	-0.190 <i>0.0534***</i>	-0.291 <i>0.0701***</i>	0.0728 <i>0.222</i>	-0.0990 <i>0.0815</i>	-0.132 <i>0.0546**</i>	-0.104 <i>0.0445**</i>	-0.0480 <i>0.0606</i>
unskilled old / unskilled young	-0.398 <i>0.110***</i>	-0.229 <i>0.0574***</i>	-0.234 <i>0.0488***</i>	-0.276 <i>0.0443***</i>	-0.217 <i>0.0556***</i>	-0.175 <i>0.0776**</i>	-0.0925 <i>0.0499*</i>	-0.0037 <i>0.0345</i>	-0.0235 <i>0.0357</i>	-0.0231 <i>0.0545</i>
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 <i>2.599</i>	-0.957 <i>0.258***</i>	-0.792 <i>0.191***</i>	-0.294 <i>0.150*</i>	-0.268 <i>0.217</i>	0.888 <i>1.343</i>	-0.602 <i>0.248**</i>	-0.0087 <i>0.118</i>	-0.176 <i>0.114</i>	0.0551 <i>0.109</i>
unskilled old / unskilled young	-0.985 <i>1.485</i>	-0.262 <i>0.219</i>	-0.157 <i>0.130</i>	-0.159 <i>0.114</i>	0.00986 <i>0.146</i>	-0.103 <i>0.750</i>	-0.465 <i>0.151***</i>	-0.0570 <i>0.0842</i>	-0.0646 <i>0.0870</i>	-0.126 <i>0.163</i>
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 <i>0.299</i>	-0.437 <i>0.104***</i>	-0.625 <i>0.0858***</i>	-0.210 <i>0.0577***</i>	-0.259 <i>0.0746***</i>	0.328 <i>0.191*</i>	0.0237 <i>0.0925</i>	-0.179 <i>0.0629***</i>	-0.101 <i>0.0499**</i>	-0.0121 <i>0.0600</i>
unskilled old / unskilled young	-0.392 <i>0.115***</i>	-0.221 <i>0.0650***</i>	-0.273 <i>0.0547***</i>	-0.356 <i>0.0482***</i>	-0.329 <i>0.0611***</i>	-0.0381 <i>0.0862</i>	-0.0038 <i>0.0569</i>	0.0110 <i>0.0410</i>	0.000142 <i>0.0412</i>	0.0230 <i>0.0605</i>
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 <i>0.409</i>	0.0462 <i>0.252</i>	-0.0092 <i>0.340</i>	0.902 <i>0.276***</i>	-0.253 <i>0.372</i>	-0.0321 <i>0.320</i>	0.0591 <i>0.252</i>	-0.115 <i>0.218</i>	0.00775 <i>0.180</i>	-0.669 <i>0.426</i>
unskilled old / unskilled young	-0.458 <i>0.178**</i>	-0.115 <i>0.144</i>	-0.239 <i>0.215</i>	0.0801 <i>0.212</i>	0.359 <i>0.311</i>	-0.361 <i>0.127***</i>	-0.202 <i>0.128</i>	0.0453 <i>0.104</i>	0.0283 <i>0.115</i>	-0.218 <i>0.202</i>
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: * $p < 0.05$, ** $p < 0.001$, *** $p < 0.001$. 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 A.2.1 – A.2.4.

Table 5

Production function estimates, ACF specifications

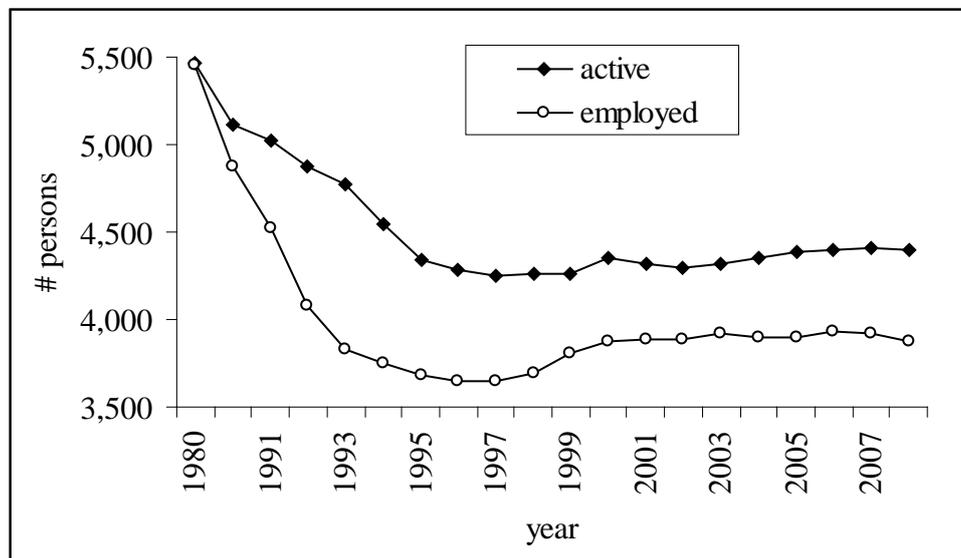
2001-2008						
ALL FIRMS						
	OLS	LP	ACF	FE	FE+LP	FE+ACF
lnK	0.228 <i>0.00547***</i>		0.269 <i>0.0431***</i>	0.0835 <i>0.00852***</i>		0.118 <i>0.0197***</i>
lnL	0.831 <i>0.00899***</i>	0.572 <i>0.0120***</i>	0.762 <i>0.020***</i>	0.632 <i>0.0171***</i>	0.541 <i>0.0190***</i>	0.645 <i>0.008***</i>
female share	-0.266 <i>0.0290***</i>	-0.0320 <i>0.0286</i>	-0.139 <i>0.079*</i>	0.0405 <i>0.0278</i>	0.0460 <i>0.0276*</i>	-0.013 <i>0.028</i>
skilled old share	-0.232 <i>0.0484***</i>	-0.145 <i>0.0456***</i>	-0.278 <i>0.0938***</i>	-0.0728 <i>0.0334**</i>	-0.0749 <i>0.0330**</i>	-0.081 <i>0.0401**</i>
unskilled young share	-1.138 <i>0.0337***</i>	-0.906 <i>0.0323***</i>	-1.060 <i>0.0787***</i>	-0.1000 <i>0.0230***</i>	-0.100 <i>0.0227***</i>	-0.137 <i>0.0300***</i>
unskilled old share	-1.392 <i>0.0401***</i>	-1.130 <i>0.0381***</i>	-1.216 <i>0.0926***</i>	-0.133 <i>0.0305***</i>	-0.128 <i>0.0303***</i>	-0.158 <i>0.0377***</i>
Obs	53,444	53,444	28,375	53,444	53,444	28,375
FOREIGN						
lnK	0.224 <i>0.0140***</i>		0.271 <i>0.148*</i>	0.0307 <i>0.0214</i>		0.081 <i>0.090</i>
lnL	0.798 <i>0.0218***</i>	0.513 <i>0.0270***</i>	0.685 <i>0.075***</i>	0.674 <i>0.0391***</i>	0.570 <i>0.0379***</i>	0.657 <i>0.0367***</i>
female share	-0.374 <i>0.0739***</i>	-0.136 <i>0.0685**</i>	-0.252 <i>0.257</i>	0.00909 <i>0.0546</i>	0.0153 <i>0.0536</i>	-0.036 <i>0.142</i>
skilled old share	-0.288 <i>0.141**</i>	-0.109 <i>0.131</i>	-0.490 <i>0.204**</i>	-0.0469 <i>0.0880</i>	-0.0520 <i>0.0860</i>	-0.144 <i>0.109</i>
unskilled young share	-1.686 <i>0.0905***</i>	-1.236 <i>0.0872***</i>	-1.408 <i>0.143***</i>	-0.130 <i>0.0470***</i>	-0.137 <i>0.0457***</i>	-0.205 <i>0.060***</i>
unskilled old share	-1.785 <i>0.113***</i>	-1.246 <i>0.108***</i>	-1.542 <i>0.205***</i>	-0.282 <i>0.0810***</i>	-0.274 <i>0.0798***</i>	-0.322 <i>0.0980***</i>
Obs	9,554	9,554	5,719	9,554	9,554	5,719
DOMESTIC						
lnK	0.228 <i>0.00583***</i>		0.263 <i>0.0484***</i>	0.106 <i>0.00961***</i>		0.138 <i>0.0215***</i>
lnL	0.849 <i>0.00979***</i>	0.604 <i>0.0134***</i>	0.784 <i>0.0202***</i>	0.617 <i>0.0196***</i>	0.524 <i>0.0221***</i>	0.654 <i>0.0111***</i>
female share	-0.191 <i>0.0315***</i>	0.0280 <i>0.0316</i>	-0.086 <i>0.092</i>	0.0625 <i>0.0339*</i>	0.0736 <i>0.0336**</i>	0.056 <i>0.0241**</i>
skilled old share	-0.230 <i>0.0515***</i>	-0.169 <i>0.0488***</i>	-0.308 <i>0.115***</i>	-0.0509 <i>0.0361</i>	-0.0519 <i>0.0356</i>	-0.005 <i>0.007</i>
unskilled young share	-1.006 <i>0.0357***</i>	-0.826 <i>0.0345***</i>	-0.942 <i>0.0980***</i>	-0.0820 <i>0.0265***</i>	-0.0817 <i>0.0262***</i>	-0.005 <i>0.007</i>
unskilled old share	-1.353 <i>0.0427***</i>	-1.134 <i>0.0407***</i>	-1.153 <i>0.113***</i>	-0.0744 <i>0.0339**</i>	-0.0732 <i>0.0337**</i>	0.025 <i>0.021</i>
Obs	40,536	40,536	19,859	40,536	40,536	19,859

Standard errors in italic, stars indicate significance levels: * $p < 0.05$, ** $p < 0.001$, *** $p < 0.001$. 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. Reference category: skilled young workers.

FIGURES

Figure 1/a

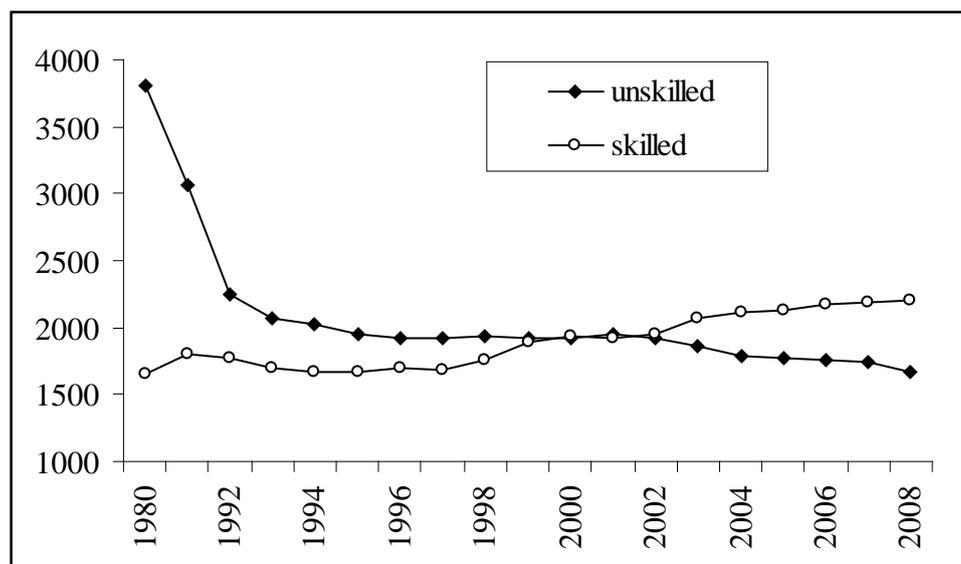
Number of active and employed persons in Hungary among the population aged over 15, thousands



Source: Central Statistical Office, stADAT

Figure 1/b

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).

APPENDIX 1: PRODUCTION FUNCTION MODEL AND METHODOLOGY

A. ESTIMATING PRODUCTIVITY DIFFERENTIALS OF WORKER GROUPS FROM PRODUCTION FUNCTIONS

The estimated form of the production function is a simplification of the one inspired by the work of Griliches (1960), and later pioneered by Hellerstein, Neumark and Troske (1999) and Hellerstein, Neumark (1999). 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 term 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 $n = 0, 1, \dots, N$ 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:

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

Thus, the production function using (2) becomes:

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

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 term³⁵. First, the number of coefficients to be estimated can be reduced by assuming that relative productivities are constant across other categories³⁶. 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 age category). Differentiating workers by gender, age (up to 45, over 45), education (college, no college) and occupation (manager, white collar, blue collar), the production function using the above simplifications becomes:

³⁵ 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.

³⁶ This means that, for example, the gender productivity gap is the same among college and no college employees; or, the productivity ratio 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.

$$\begin{aligned} \ln VA_{jt} = & \beta_0 + \beta_1 \ln K_{jt} + \beta_2 \ln \varphi_0 + \beta_2 \ln L_{jt} + \beta_2 \ln \left[1 + (\varphi_F - 1) l_{F_{jt}} \right] + \beta_2 \ln \left[1 + (\varphi_E - 1) l_{E_{jt}} \right] \\ & + \beta_2 \ln \left[1 + (\varphi_O - 1) l_{O_{jt}} \right] + \beta_2 \ln \left[1 + (\varphi_W - 1) l_{W_{jt}} + (\varphi_M - 1) l_{M_{jt}} \right] + \lambda \cdot X_{jt} + \varepsilon_{jt} \end{aligned} \quad (4)$$

where φ_F is the productivity of women relative to men, φ_E is the productivity of educated workers relative to uneducated workers, and φ_O is the relative productivity of the over 45 age groups relative to the up to 45 age category, and φ_W and φ_M are the relative productivities of white collar workers and managers relative to blue collar workers. The proportion of workers in each group are denoted by the l_k variables ($k = F, E, O, W, M$).

After linear approximation, equation (4) becomes³⁷:

$$\begin{aligned} \ln VA_{jt} = & \beta_0 + \beta_1 \ln K_{jt} + \beta_2 \ln \varphi_0 + \beta_2 \ln L_{jt} + \gamma_F l_{F_{jt}} + \gamma_E l_{E_{jt}} \\ & + \gamma_O l_{O_{jt}} + \gamma_W l_{W_{jt}} + \gamma_M l_{M_{jt}} + \lambda \cdot X_{jt} + \varepsilon_{jt} \end{aligned} \quad (5)$$

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 ($k = F, E, O, W, M$) in equation (5) cannot 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 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 our study concentrates on assessing how productivity is related to age, we obtain estimates of the γ_k parameters, but do not compute relative productivities. However, we compare the obtained γ_k coefficients of the various categories with each other and interpret, for example, $\gamma_Y > \gamma_O$ as the younger age group being more productive than the older one. Thus, when we talk about the productivity of the different worker groups, we are referring to the estimated γ_k parameters.

³⁷ Assuming that $(\varphi_F - 1) \frac{L_F}{L} < 0.1$ 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) apply the linear approximation, including Dostie (2006), Ilmakunnas and Maliranta (2003), Crepon et al (2002), Ours and Stoeldraijer (2010), Borowczyk and Vandenberghe (2010) or Vandenberghe and Waltenberg (2010).

B. SIMULTANEITY AND THE STRUCTURAL METHODS (LEVINSOHN AND PETRIN 2003, ACKERBERG, CAVES AND FRAZER 2006)

In our final specifications we apply a method that 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; Akerberg, 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:

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

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 $g(\cdot)$ proxy function and the capital term of the production function as it cannot be identified separately due to collinearity issues. We can estimate equation (6) approximating $\psi(\cdot)$ by third order polynomials:

$$\ln VA_{jt} = \beta_0 + \beta_2 \cdot \ln L_{jt} + \sum_k \gamma_k \cdot I_{k_{jt}} + \lambda \cdot X + \sum_{p=0}^3 \sum_{q=0}^{3-p} \delta_{pq} \cdot (\ln K_{jt})^p (\ln M_{jt})^q + \varepsilon_{jt} \quad (7)$$

Equation (7) 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 follows³⁸. First, assume that productivity follows a first order Markov process:

³⁸ As our primary interests are the estimates of the workers composition variables, we do not compute the second-stage capital coefficient.

$$\omega_{jt} = E[\omega_{jt} | I_{jt-1}] + \xi_{jt} = E[\omega_{jt} | \omega_{jt-1}] + \xi_{jt} = g(\omega_{jt-1}) + \xi_{jt}. \quad (8)$$

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:

$$\omega_{jt} = \hat{\Psi}_{jt} - \beta_1 \cdot \ln K_{jt}. \quad (9)$$

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 minimized³⁹.

The linearity of the first stage equation (7) offers the opportunity to include firm fixed effects into LP's model when estimating the labor and the worker share coefficients. We remove firm fixed effects at this stage by time demeaning the variables in equation (7)⁴⁰.

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 does not vary independently from the $g(\cdot)$ 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

³⁹ 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.

⁴⁰ 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.

to the timing assumption, the demand for material costs is also a function of labor and the worker share variables:

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

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:

$$\ln VA_{jt} = \Psi(\ln K_{jt}, \ln M_{jt}, \ln L_{jt}, l_1, \dots, l_k, \dots) + \varepsilon_{jt} \quad (10)$$

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

Equation (10) is estimated by using a third-order polynomial approximation of the $\psi(\cdot)$ 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:

$$\omega_{jt} = E[\omega_{jt} | I_{jt-1}] + \xi_{jt} = E[\omega_{jt} | \omega_{jt-1}] + \xi_{jt} = g(\omega_{jt-1}) + \xi_{jt} \quad (11)$$

In the above expression ξ_{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:

$$E \left[\begin{array}{c} \ln K_{jt} \\ \ln L_{jt-1} \\ \xi_{jt} | l_{jt-1}^1 \\ \vdots \\ l_{jt-1}^k \end{array} \right] = 0 \quad (12)$$

As ACF notes, the researcher may alternatively assume that the labor inputs were chosen at or prior to $t - 1$.⁴¹ Hence, an alternative set of identifying moment conditions are:

⁴¹ 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”.

$$E \begin{bmatrix} \ln K_{jt} \\ \ln L_{jt} \\ \xi_{jt} \mid l_{jt}^1 \\ \vdots \\ l_{jt}^k \end{bmatrix} = 0 \quad (13)$$

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

$$\omega_{jt} = \hat{\Psi}_{jt} - \beta_1^0 \cdot \ln K_{jt} - \beta_2^0 \cdot \ln L_{jt} - \sum_k \gamma_k^0 \cdot l_k \quad (14)$$

Then, we apply the formula in (8) 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, we estimate equation (10) via the fixed effect estimator⁴², 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 effects⁴³.

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 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 (12)⁴⁴. As the ACF results on our subsamples, covering only 2 to 5 years of observations divided by ownership type, were often estimated with huge standard errors, we could not apply the ACF method in each period. However, in order to get an idea about the possible differences compared to the other methods, we pooled our last two periods, and provide both OLS, LP, ACF, FE, FE+LP and FE+ACF estimates for 2001-2008. In case of the ACF estimates, we use the moment conditions described by (13). The full set of estimation results are shown in Table 5, and a short analysis of the results is provided in the Results section of the paper.

⁴² Alternatively, one can also use first-differencing.

⁴³ For more information on the FE+ACF method, see Rigo, Vandenberghe and Waltenberg (2011).

⁴⁴ 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 A.2.1.

APPENDIX 2: FULL ESTIMATION RESULTS OF THE UNRESTRICTED SPECIFICATIONS

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 <i>0.0182***</i>	0.130 <i>0.00828***</i>	0.220 <i>0.00746***</i>	0.233 <i>0.00619***</i>	0.222 <i>0.00724***</i>					
lnL	0.637 <i>0.0238***</i>	0.857 <i>0.0136***</i>	0.807 <i>0.0113***</i>	0.822 <i>0.00989***</i>	0.844 <i>0.0121***</i>	0.209 <i>0.0292***</i>	0.542 <i>0.0645***</i>	0.520 <i>0.0276***</i>	0.542 <i>0.0264***</i>	0.547 <i>0.0396***</i>
female share	0.438 <i>0.0939***</i>	-0.0500 <i>0.0321</i>	-0.204 <i>0.0391***</i>	-0.242 <i>0.0328***</i>	-0.303 <i>0.0397***</i>	0.278 <i>0.0924***</i>	0.0195 <i>0.0212</i>	0.00146 <i>0.0388</i>	0.0871 <i>0.0375**</i>	0.0205 <i>0.0454</i>
skilled old share	0.283 <i>0.290</i>	-0.483 <i>0.0916***</i>	-0.645 <i>0.0762***</i>	-0.190 <i>0.0534***</i>	-0.291 <i>0.0701***</i>	0.0728 <i>0.222</i>	-0.0990 <i>0.0815</i>	-0.132 <i>0.0546**</i>	-0.104 <i>0.0445**</i>	-0.0480 <i>0.0606</i>
unskilled young share	-0.747 <i>0.122***</i>	-1.183 <i>0.0584***</i>	-1.419 <i>0.0484***</i>	-1.127 <i>0.0385***</i>	-1.152 <i>0.0465***</i>	0.141 <i>0.102</i>	-0.0487 <i>0.0587</i>	-0.0687 <i>0.0370*</i>	-0.0959 <i>0.0320***</i>	-0.0518 <i>0.0342</i>
unskilled old share	-1.145 <i>0.135***</i>	-1.412 <i>0.0685***</i>	-1.653 <i>0.0558***</i>	-1.403 <i>0.0451***</i>	-1.369 <i>0.0543***</i>	-0.0338 <i>0.109</i>	-0.141 <i>0.0683**</i>	-0.0724 <i>0.0454</i>	-0.119 <i>0.0407***</i>	-0.0749 <i>0.0526</i>
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: * $p < 0.05$, ** $p < 0.001$, *** $p < 0.001$. 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 A.2.2.

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					
	<i>0.0249***</i>	<i>0.00933***</i>	<i>0.00838***</i>	<i>0.00672***</i>	<i>0.00765***</i>					
lnL	0.647	0.859	0.828	0.836	0.870	0.204	0.632	0.539	0.527	0.547
	<i>0.0307***</i>	<i>0.0158***</i>	<i>0.0131***</i>	<i>0.0110***</i>	<i>0.0129***</i>	<i>0.0278***</i>	<i>0.0485***</i>	<i>0.0318***</i>	<i>0.0304***</i>	<i>0.0462***</i>
female share	0.239	-0.101	-0.220	-0.180	-0.210	0.229	0.00158	0.0600	0.0957	0.0232
	<i>0.127*</i>	<i>0.0372***</i>	<i>0.0453***</i>	<i>0.0364***</i>	<i>0.0437***</i>	<i>0.132*</i>	<i>0.0253</i>	<i>0.0470</i>	<i>0.0471**</i>	<i>0.0540</i>
skilled old share	0.338	-0.437	-0.625	-0.210	-0.259	0.328	0.0237	-0.179	-0.101	-0.0121
	<i>0.299</i>	<i>0.104***</i>	<i>0.0858***</i>	<i>0.0577***</i>	<i>0.0746***</i>	<i>0.191*</i>	<i>0.0925</i>	<i>0.0629***</i>	<i>0.0499**</i>	<i>0.0600</i>
unskilled young share	-0.694	-1.032	-1.299	-1.013	-0.994	0.127	-0.00996	-0.0708	-0.0900	-0.0379
	<i>0.145***</i>	<i>0.0715***</i>	<i>0.0562***</i>	<i>0.0419***</i>	<i>0.0501***</i>	<i>0.111</i>	<i>0.0690</i>	<i>0.0439</i>	<i>0.0370**</i>	<i>0.0405</i>
unskilled old share	-0.302	-1.253	-1.573	-1.370	-1.322	0.166	-0.0137	-0.0598	-0.0899	-0.0149
	<i>0.135**</i>	<i>0.0819***</i>	<i>0.0652***</i>	<i>0.0486***</i>	<i>0.0593***</i>	<i>0.103</i>	<i>0.0846</i>	<i>0.0532</i>	<i>0.0471*</i>	<i>0.0592</i>
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<0.05, **p<0.001, ***p<0.001. 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 A.2.3.

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 <i>0.160***</i>	0.262 <i>0.0314***</i>	0.274 <i>0.0173***</i>	0.235 <i>0.0149***</i>	0.209 <i>0.0207***</i>					
lnL	0.543 <i>0.207***</i>	0.726 <i>0.0423***</i>	0.730 <i>0.0237***</i>	0.798 <i>0.0227***</i>	0.793 <i>0.0330***</i>	0.811 <i>0.433*</i>	0.434 <i>0.0926***</i>	0.505 <i>0.0518***</i>	0.576 <i>0.0532***</i>	0.498 <i>0.0787***</i>
female share	1.221 <i>0.906</i>	0.0808 <i>0.0927</i>	-0.179 <i>0.0893**</i>	-0.326 <i>0.0825***</i>	-0.441 <i>0.0955***</i>	0.419 <i>0.831</i>	0.0343 <i>0.0580</i>	-0.111 <i>0.0736</i>	0.0954 <i>0.0679</i>	0.0202 <i>0.0840</i>
skilled old share	-1.916 <i>2.599</i>	-0.957 <i>0.258***</i>	-0.792 <i>0.191***</i>	-0.294 <i>0.150*</i>	-0.268 <i>0.217</i>	0.888 <i>1.343</i>	-0.602 <i>0.248**</i>	-0.00867 <i>0.118</i>	-0.176 <i>0.114</i>	0.0551 <i>0.109</i>
unskilled young share	-1.421 <i>1.152</i>	-1.703 <i>0.156***</i>	-1.708 <i>0.104***</i>	-1.652 <i>0.101***</i>	-1.742 <i>0.120***</i>	0.405 <i>0.630</i>	-0.0698 <i>0.141</i>	-0.0227 <i>0.0700</i>	-0.126 <i>0.0667*</i>	-0.0680 <i>0.0602</i>
unskilled old share	-0.436 <i>0.989</i>	-1.965 <i>0.225***</i>	-1.864 <i>0.135***</i>	-1.811 <i>0.124***</i>	-1.732 <i>0.144***</i>	0.508 <i>0.557</i>	-0.535 <i>0.175***</i>	-0.0797 <i>0.0930</i>	-0.190 <i>0.0958**</i>	-0.194 <i>0.150</i>
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<0.05, **p<0.001, ***p<0.001. 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 A.2.4.

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 <i>0.0228***</i>	0.0770 <i>0.0214***</i>	0.156 <i>0.0438***</i>	0.249 <i>0.0379***</i>	0.282 <i>0.0388***</i>					
lnL	0.617 <i>0.0308***</i>	0.924 <i>0.0341***</i>	0.807 <i>0.0560***</i>	0.751 <i>0.0579***</i>	0.698 <i>0.0692***</i>	0.186 <i>0.0425***</i>	0.893 <i>0.114***</i>	0.422 <i>0.118***</i>	0.445 <i>0.194**</i>	0.697 <i>0.274**</i>
female share	0.458 <i>0.125***</i>	0.284 <i>0.0882***</i>	0.0611 <i>0.172</i>	-0.514 <i>0.209**</i>	-0.617 <i>0.245**</i>	0.264 <i>0.131**</i>	0.182 <i>0.0691***</i>	0.0350 <i>0.123</i>	-0.0615 <i>0.147</i>	0.181 <i>0.202</i>
skilled old share	0.184 <i>0.409</i>	0.0462 <i>0.252</i>	-0.00921 <i>0.340</i>	0.902 <i>0.276***</i>	-0.253 <i>0.372</i>	-0.0321 <i>0.320</i>	0.0591 <i>0.252</i>	-0.115 <i>0.218</i>	0.00775 <i>0.180</i>	-0.669 <i>0.426</i>
unskilled young share	-1.010 <i>0.172***</i>	-0.897 <i>0.164***</i>	-1.300 <i>0.232***</i>	-0.628 <i>0.248**</i>	-1.008 <i>0.340***</i>	0.136 <i>0.147</i>	-0.0849 <i>0.135</i>	-0.102 <i>0.163</i>	-0.0964 <i>0.178</i>	-0.222 <i>0.178</i>
unskilled old share	-1.468 <i>0.196***</i>	-1.012 <i>0.173***</i>	-1.538 <i>0.251***</i>	-0.547 <i>0.262**</i>	-0.650 <i>0.296**</i>	-0.225 <i>0.169</i>	-0.287 <i>0.153*</i>	-0.0562 <i>0.180</i>	-0.0682 <i>0.174</i>	-0.440 <i>0.240*</i>
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: * $p < 0.05$, ** $p < 0.001$, *** $p < 0.001$. 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 A.2.5.

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 <i>0.0180***</i>	0.144 <i>0.00837***</i>	0.235 <i>0.00743***</i>	0.242 <i>0.00613***</i>	0.228 <i>0.00711***</i>					
lnL	0.626 <i>0.0233***</i>	0.836 <i>0.0136***</i>	0.776 <i>0.0114***</i>	0.795 <i>0.00976***</i>	0.821 <i>0.0118***</i>	0.214 <i>0.0284***</i>	0.541 <i>0.0645***</i>	0.522 <i>0.0275***</i>	0.542 <i>0.0263***</i>	0.544 <i>0.0396***</i>
female share	0.551 <i>0.0917***</i>	0.0327 <i>0.0331</i>	-0.0520 <i>0.0398</i>	-0.0968 <i>0.0331***</i>	-0.144 <i>0.0399***</i>	0.229 <i>0.0827***</i>	0.0211 <i>0.0213</i>	0.00882 <i>0.0389</i>	0.0967 <i>0.0378**</i>	0.0301 <i>0.0451</i>
skilled old share	-0.454 <i>0.823</i>	-1.005 <i>0.179***</i>	-0.887 <i>0.157***</i>	-0.458 <i>0.107***</i>	-0.421 <i>0.152***</i>	0.603 <i>0.646</i>	-0.144 <i>0.175</i>	-0.220 <i>0.114*</i>	-0.114 <i>0.0938</i>	0.0287 <i>0.122</i>
unskilled young share	-2.180 <i>0.305***</i>	-1.906 <i>0.112***</i>	-2.115 <i>0.0901***</i>	-1.722 <i>0.0656***</i>	-1.649 <i>0.0735***</i>	0.123 <i>0.299</i>	-0.116 <i>0.170</i>	-0.209 <i>0.0765***</i>	-0.198 <i>0.0632***</i>	0.00941 <i>0.0560</i>
unskilled old share	-2.567 <i>0.312***</i>	-2.149 <i>0.116***</i>	-2.446 <i>0.0920***</i>	-2.000 <i>0.0676***</i>	-1.948 <i>0.0768***</i>	-0.0173 <i>0.300</i>	-0.205 <i>0.167</i>	-0.238 <i>0.0796***</i>	-0.245 <i>0.0684***</i>	-0.0337 <i>0.0706</i>
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: * $p < 0.05$, ** $p < 0.001$, *** $p < 0.001$. 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 A.2.6.

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 <i>0.0249***</i>	0.137 <i>0.00926***</i>	0.224 <i>0.00830***</i>	0.237 <i>0.00670***</i>	0.228 <i>0.00763***</i>					
lnL	0.625 <i>0.0303***</i>	0.839 <i>0.0157***</i>	0.797 <i>0.0131***</i>	0.807 <i>0.0109***</i>	0.844 <i>0.0128***</i>	0.208 <i>0.0268***</i>	0.632 <i>0.0484***</i>	0.544 <i>0.0318***</i>	0.527 <i>0.0304***</i>	0.545 <i>0.0462***</i>
female share	0.328 <i>0.125***</i>	-0.0256 <i>0.0382</i>	-0.0840 <i>0.0458*</i>	-0.0431 <i>0.0369</i>	-0.0726 <i>0.0442</i>	0.204 <i>0.131</i>	0.00372 <i>0.0253</i>	0.0654 <i>0.0470</i>	0.104 <i>0.0474**</i>	0.0312 <i>0.0535</i>
skilled old share	0.263 <i>0.846</i>	-0.957 <i>0.220***</i>	-1.126 <i>0.179***</i>	-0.472 <i>0.120***</i>	-0.477 <i>0.167***</i>	0.450 <i>0.600</i>	-0.143 <i>0.235</i>	-0.333 <i>0.143**</i>	-0.106 <i>0.113</i>	0.0273 <i>0.127</i>
unskilled young share	-0.302 <i>0.360</i>	-1.803 <i>0.149***</i>	-2.249 <i>0.108***</i>	-1.615 <i>0.0788***</i>	-1.562 <i>0.0881***</i>	0.304 <i>0.393</i>	-0.199 <i>0.197</i>	-0.306 <i>0.105***</i>	-0.175 <i>0.0869**</i>	0.0893 <i>0.0740</i>
unskilled old share	-0.657 <i>0.357*</i>	-2.025 <i>0.152***</i>	-2.592 <i>0.111***</i>	-1.961 <i>0.0793***</i>	-1.916 <i>0.0912***</i>	0.323 <i>0.371</i>	-0.186 <i>0.199</i>	-0.333 <i>0.107***</i>	-0.206 <i>0.0908**</i>	0.0965 <i>0.0843</i>
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<0.05, **p<0.001, ***p<0.001. 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 A.2.7.

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					
	<i>0.163***</i>	<i>0.0324***</i>	<i>0.0170***</i>	<i>0.0141***</i>	<i>0.0205***</i>					
lnL	0.522	0.678	0.714	0.776	0.776	0.749	0.426	0.504	0.585	0.494
	<i>0.208**</i>	<i>0.0441***</i>	<i>0.0241***</i>	<i>0.0217***</i>	<i>0.0318***</i>	<i>0.420*</i>	<i>0.0910***</i>	<i>0.0516***</i>	<i>0.0525***</i>	<i>0.0800***</i>
female share	1.243	0.0421	-0.114	-0.204	-0.241	-0.0575	0.0321	-0.106	0.103	0.0328
	<i>0.897</i>	<i>0.0979</i>	<i>0.0917</i>	<i>0.0807**</i>	<i>0.0945**</i>	<i>0.704</i>	<i>0.0572</i>	<i>0.0738</i>	<i>0.0684</i>	<i>0.0831</i>
skilled old share	-1.043	-1.532	-0.326	-0.110	0.176	-4.218	-0.536	0.0131	-0.0468	0.0560
	<i>6.783</i>	<i>0.450***</i>	<i>0.336</i>	<i>0.262</i>	<i>0.442</i>	<i>3.956</i>	<i>0.439</i>	<i>0.199</i>	<i>0.188</i>	<i>0.205</i>
unskilled young share	0.165	-1.767	-1.830	-1.919	-1.805	-2.599	0.133	-0.0379	-0.234	-0.0746
	<i>2.448</i>	<i>0.221***</i>	<i>0.155***</i>	<i>0.129***</i>	<i>0.143***</i>	<i>1.353*</i>	<i>0.310</i>	<i>0.103</i>	<i>0.0858***</i>	<i>0.0772</i>
unskilled old share	-1.132	-2.169	-2.256	-2.202	-2.049	-1.239	-0.388	-0.0812	-0.346	-0.148
	<i>2.204</i>	<i>0.273***</i>	<i>0.165***</i>	<i>0.143***</i>	<i>0.160***</i>	<i>1.104</i>	<i>0.375</i>	<i>0.121</i>	<i>0.111***</i>	<i>0.147</i>
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: * $p < 0.05$, ** $p < 0.001$, *** $p < 0.001$. 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 A.2.8.

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 <i>0.0224***</i>	0.0830 <i>0.0212***</i>	0.175 <i>0.0438***</i>	0.259 <i>0.0370***</i>	0.291 <i>0.0372***</i>					
lnL	0.608 <i>0.0301***</i>	0.915 <i>0.0333***</i>	0.773 <i>0.0560***</i>	0.746 <i>0.0576***</i>	0.688 <i>0.0672***</i>	0.187 <i>0.0416***</i>	0.880 <i>0.113***</i>	0.427 <i>0.118***</i>	0.443 <i>0.194**</i>	0.762 <i>0.292***</i>
female share	0.616 <i>0.123***</i>	0.416 <i>0.0885***</i>	0.478 <i>0.165***</i>	-0.258 <i>0.201</i>	-0.409 <i>0.223*</i>	0.217 <i>0.109**</i>	0.196 <i>0.0701***</i>	0.0648 <i>0.136</i>	-0.0497 <i>0.148</i>	0.201 <i>0.196</i>
skilled old share	-0.784 <i>1.049</i>	0.0417 <i>0.566</i>	-1.247 <i>0.813</i>	0.401 <i>0.651</i>	-0.0325 <i>0.719</i>	0.946 <i>0.902</i>	0.0801 <i>0.508</i>	-0.606 <i>0.553</i>	-0.130 <i>0.621</i>	0.260 <i>0.793</i>
unskilled young share	-2.727 <i>0.378***</i>	-1.446 <i>0.380***</i>	-2.373 <i>0.490***</i>	-1.020 <i>0.492**</i>	-0.674 <i>0.475</i>	0.193 <i>0.360</i>	-0.486 <i>0.465</i>	-0.377 <i>0.436</i>	0.0334 <i>0.387</i>	-0.318 <i>0.386</i>
unskilled old share	-3.215 <i>0.392***</i>	-1.563 <i>0.373***</i>	-2.471 <i>0.517***</i>	-0.611 <i>0.469</i>	-0.613 <i>0.439</i>	-0.145 <i>0.376</i>	-0.618 <i>0.443</i>	-0.332 <i>0.429</i>	0.0568 <i>0.396</i>	-0.780 <i>0.543</i>
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: * $p < 0.05$, ** $p < 0.001$, *** $p < 0.001$. 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 A.2.9.

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 <i>0.0180***</i>	0.129 <i>0.00825***</i>	0.212 <i>0.00728***</i>	0.223 <i>0.00603***</i>	0.214 <i>0.00708***</i>					
lnL	0.643 <i>0.0242***</i>	0.857 <i>0.0136***</i>	0.824 <i>0.0111***</i>	0.843 <i>0.00971***</i>	0.861 <i>0.0118***</i>	0.213 <i>0.0295***</i>	0.546 <i>0.0647***</i>	0.522 <i>0.0276***</i>	0.553 <i>0.0266***</i>	0.545 <i>0.0395***</i>
female share	-0.159 <i>0.0923*</i>	-0.120 <i>0.0325***</i>	-0.385 <i>0.0407***</i>	-0.450 <i>0.0334***</i>	-0.458 <i>0.0416***</i>	0.275 <i>0.0969***</i>	0.0112 <i>0.0209</i>	-0.0117 <i>0.0398</i>	0.0687 <i>0.0396*</i>	0.0453 <i>0.0483</i>
skilled old share	-0.115 <i>0.280</i>	-0.555 <i>0.0916***</i>	-0.731 <i>0.0738***</i>	-0.293 <i>0.0527***</i>	-0.318 <i>0.0672***</i>	0.0841 <i>0.221</i>	-0.105 <i>0.0824</i>	-0.140 <i>0.0545***</i>	-0.116 <i>0.0453**</i>	-0.0551 <i>0.0623</i>
unskilled young share	-0.238 <i>0.144*</i>	-0.742 <i>0.0683***</i>	-0.661 <i>0.0571***</i>	-0.381 <i>0.0420***</i>	-0.400 <i>0.0517***</i>	0.160 <i>0.137</i>	-0.00758 <i>0.0593</i>	-0.0250 <i>0.0367</i>	-0.0501 <i>0.0313</i>	-0.0604 <i>0.0353*</i>
unskilled old share	-0.520 <i>0.153***</i>	-0.975 <i>0.0754***</i>	-0.910 <i>0.0630***</i>	-0.632 <i>0.0474***</i>	-0.611 <i>0.0569***</i>	-0.0113 <i>0.149</i>	-0.0934 <i>0.0690</i>	-0.0235 <i>0.0459</i>	-0.0689 <i>0.0398*</i>	-0.0871 <i>0.0528**</i>
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: * $p < 0.05$, ** $p < 0.001$, *** $p < 0.001$. 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 A.2.10.

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					
	<i>0.0237***</i>	<i>0.00933***</i>	<i>0.00823***</i>	<i>0.00658***</i>	<i>0.00753***</i>					
lnL	0.653	0.857	0.843	0.857	0.889	0.204	0.644	0.541	0.535	0.545
	<i>0.0285***</i>	<i>0.0158***</i>	<i>0.0128***</i>	<i>0.0108***</i>	<i>0.0127***</i>	<i>0.0272***</i>	<i>0.0479***</i>	<i>0.0318***</i>	<i>0.0307***</i>	<i>0.0458***</i>
female share	-0.184	-0.160	-0.416	-0.436	-0.413	0.210	-0.0101	0.0369	0.0849	0.0576
	<i>0.109*</i>	<i>0.0380***</i>	<i>0.0485***</i>	<i>0.0383***</i>	<i>0.0467***</i>	<i>0.136</i>	<i>0.0250</i>	<i>0.0475</i>	<i>0.0498*</i>	<i>0.0578</i>
skilled old share	0.114	-0.516	-0.752	-0.323	-0.302	0.321	-0.00325	-0.201	-0.113	-0.00826
	<i>0.277</i>	<i>0.104***</i>	<i>0.0830***</i>	<i>0.0571***</i>	<i>0.0726***</i>	<i>0.185*</i>	<i>0.0934</i>	<i>0.0629***</i>	<i>0.0506**</i>	<i>0.0619</i>
unskilled young share	-0.0564	-0.607	-0.691	-0.387	-0.386	0.173	0.0374	-0.0163	-0.0658	-0.0561
	<i>0.176</i>	<i>0.0792***</i>	<i>0.0650***</i>	<i>0.0452***</i>	<i>0.0553***</i>	<i>0.131</i>	<i>0.0766</i>	<i>0.0434</i>	<i>0.0360*</i>	<i>0.0420</i>
unskilled old share	-0.256	-0.835	-0.954	-0.691	-0.673	0.151	0.0313	-0.00312	-0.0593	-0.0365
	<i>0.187</i>	<i>0.0885***</i>	<i>0.0723***</i>	<i>0.0512***</i>	<i>0.0619***</i>	<i>0.142</i>	<i>0.0889</i>	<i>0.0537</i>	<i>0.0461</i>	<i>0.0596</i>
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: * $p < 0.05$, ** $p < 0.001$, *** $p < 0.001$. 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 A.2.11.

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 <i>0.183***</i>	0.265 <i>0.0314***</i>	0.266 <i>0.0170***</i>	0.229 <i>0.0144***</i>	0.208 <i>0.0199***</i>					
lnL	0.297 <i>0.227</i>	0.720 <i>0.0424***</i>	0.759 <i>0.0232***</i>	0.826 <i>0.0218***</i>	0.810 <i>0.0305***</i>	1.063 <i>0.329***</i>	0.437 <i>0.0907***</i>	0.500 <i>0.0519***</i>	0.596 <i>0.0517***</i>	0.497 <i>0.0804***</i>
female share	0.449 <i>0.838</i>	0.0185 <i>0.0906</i>	-0.269 <i>0.0842***</i>	-0.309 <i>0.0746***</i>	-0.360 <i>0.0918***</i>	0.00350 <i>0.897</i>	0.0285 <i>0.0591</i>	-0.0810 <i>0.0760</i>	0.0778 <i>0.0696</i>	0.0417 <i>0.0912</i>
skilled old share	-1.516 <i>2.291</i>	-0.967 <i>0.260***</i>	-0.722 <i>0.179***</i>	-0.324 <i>0.145**</i>	-0.123 <i>0.195</i>	2.450 <i>1.099**</i>	-0.590 <i>0.253**</i>	-0.00411 <i>0.117</i>	-0.178 <i>0.116</i>	0.0602 <i>0.110</i>
unskilled young share	-0.0888 <i>1.370</i>	-1.234 <i>0.225***</i>	-0.524 <i>0.120***</i>	-0.452 <i>0.117***</i>	-0.512 <i>0.144***</i>	1.577 <i>1.083</i>	-0.0554 <i>0.139</i>	-0.0664 <i>0.0718</i>	0.0209 <i>0.0638</i>	-0.0675 <i>0.0652</i>
unskilled old share	-1.492 <i>1.424</i>	-1.530 <i>0.260***</i>	-0.779 <i>0.150***</i>	-0.694 <i>0.134***</i>	-0.629 <i>0.157***</i>	1.613 <i>1.166</i>	-0.531 <i>0.170***</i>	-0.121 <i>0.0974</i>	-0.0479 <i>0.0852</i>	-0.199 <i>0.147</i>
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<0.05, **p<0.001, ***p<0.001. 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 A.2.12.

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					
	<i>0.0229***</i>	<i>0.0211***</i>	<i>0.0398***</i>	<i>0.0355***</i>	<i>0.0370***</i>					
lnL	0.631	0.941	0.841	0.790	0.737	0.192	0.877	0.420	0.454	0.763
	<i>0.0319***</i>	<i>0.0339***</i>	<i>0.0524***</i>	<i>0.0548***</i>	<i>0.0661***</i>	<i>0.0437***</i>	<i>0.109***</i>	<i>0.115***</i>	<i>0.197**</i>	<i>0.276***</i>
female share	-0.215	0.162	-0.261	-0.901	-0.733	0.272	0.183	0.0713	0.00415	-0.0214
	<i>0.135</i>	<i>0.0964*</i>	<i>0.196</i>	<i>0.213***</i>	<i>0.273***</i>	<i>0.138**</i>	<i>0.0716**</i>	<i>0.138</i>	<i>0.182</i>	<i>0.241</i>
skilled old share	-0.199	0.00905	-0.277	0.858	-0.239	-0.0221	0.110	-0.0734	-0.0469	-0.877
	<i>0.396</i>	<i>0.258</i>	<i>0.291</i>	<i>0.247***</i>	<i>0.347</i>	<i>0.317</i>	<i>0.271</i>	<i>0.221</i>	<i>0.220</i>	<i>0.449*</i>
unskilled young share	-0.330	-0.467	-0.410	0.260	-0.0243	0.183	-0.100	-0.104	-0.118	-0.108
	<i>0.204</i>	<i>0.168***</i>	<i>0.247*</i>	<i>0.265</i>	<i>0.364</i>	<i>0.222</i>	<i>0.152</i>	<i>0.136</i>	<i>0.219</i>	<i>0.234</i>
unskilled old share	-0.769	-0.551	-0.669	0.416	0.301	-0.182	-0.289	-0.0360	-0.120	-0.288
	<i>0.221***</i>	<i>0.183***</i>	<i>0.276**</i>	<i>0.264</i>	<i>0.336</i>	<i>0.246</i>	<i>0.175*</i>	<i>0.162</i>	<i>0.228</i>	<i>0.261</i>
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: * $p < 0.05$, ** $p < 0.001$, *** $p < 0.001$. 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.

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