WAGES AND FOREIGN DIRECT INVESTMENT IN HUNGARY

by
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Gábor Antal

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ABSTRACT

The thesis consists of three self-standing papers organized into three chapters. All three rely on the same data source, yet I use slightly different samples in each of them. All of the work in this dissertation deals with relative wages and/or the distribution of wages in Hungary, and the second and third papers focus on the relationship between foreign ownership and wages in particular.
Also, since the papers were written with the future goal of publication in peer-reviewed journals, I kept them as separate entities for the purpose of thesis submission as well. Thus, each chapter can be read of its own. Where necessary, cross-referencing between the papers was applied. The abstract of each chapter follows below.

Chapter 1: Dispersion of Wages in Transition: Trends and Reasons of Changes in Wage Inequality in the Hungarian Business Sector, 1986-2008

Exploiting a large linked employer-employee dataset of 2.8 million observations on workers employed by 37,000 enterprises, I study earnings inequality of full-time employees in the Hungarian business sector. I find that the dispersion of real monthly earnings – as measured by several inequality indices – increased rapidly from 1989 to 2000, then declined significantly until 2002, started to rise again shortly, but returned to a decreasing path in 2005. At its peak level, wage inequality was the highest among OECD countries. Within-firm variance constantly declined throughout the period while all changes in total wage dispersion are reflected in between-firm variance. This is to some extent explained by differences in within-cohort variances of new entrant firms. Half of the decline between 2000 and 2002 is explained by a 57 per cent increase in the real value of the minimum wage. Between 2002 and 2008, when measures on working hours are available, I do not find any evidence of working hours explaining trends in inequality of monthly earnings. Results do not change significantly when controlling for the changing size criteria of sample inclusion for companies across years. The contribution of changes in skill composition is around 30%, mainly due to the increasing dominance of high-skilled workers in terms of growing employment shares, group-level inequality and mean wages. Yet, a large part of inequality changes remains unexplained by observable factors.

Chapter 2: The Effect of Foreign Acquisitions on Wages: Evidence from Hungarian Firm and Linked Employer-Employee Data
(joint with John Earle and Álmos Telegdy)

This paper estimates the effects of foreign acquisitions on average and worker-specific wages in previously domestically owned firms in Hungary. The analysis is carried out both at the firm level using universal data for all Hungarian corporations and at the worker level using linked employer-employee data from a very large survey. The panel is much longer (23 years) than in previous studies and the data contain a large number of foreign acquisitions with information both before and after the change in ownership. Our empirical methods include matching on multiple years of pre-acquisition data and fixed effects for firms, detailed worker groups, and individuals (where workers can be linked inside firms). We also exploit reversals in ownership status: acquisition followed later by divestment. While point estimates are sensitive to specification, we find in all cases positive effects of FDI on average wages, and even on wages of all worker types. The only significantly higher foreign premium is associated with university education. We consider possible explanations for the findings, including productivity and rent-sharing, as well as selection and

measurement. The evidence suggests that the foreign premium is strongly associated with a similar differential in productivity.

Chapter 3: Foreign Ownership and the Distribution of Wages in Hungary, 1992-2000: An Unconditional Quantile Decomposition Approach

With the help of a rich linked dataset on both firms and workers of the Hungarian corporate sector, this paper analyzes how changes in foreign direct investment contributed to changes in the unconditional wage distribution at different quantiles between 1992 and 2000. After transition, Hungary experienced an extraordinary amount of continuous FDI inflow during the nineties, while earnings inequality increased by close to seventy percent in just ten years, compared to its 1989 level. The role of FDI in inequality changes is partialed out by a detailed decomposition of log wage changes based on a recently developed method by Firpo et al. (2009) that extends the standard Oaxaca-Blinder decomposition to unconditional quantiles of the distribution. I find that at every point in time, the share of employees of foreign-owned firms has a positive and significant wage level effect at every unconditional quantile, and these effects are inequality enhancing for men while they have an ambiguous effect on the unconditional dispersion for women. FDI contributed strongly to wage changes at every part of the distribution through an increased foreign employment share in the economy, but not through changes in the returns to being employed by foreign-owned firms. However, it played only a moderate role in the growth of inequality.

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CHAPTER ONE

1. Dispersion of Wages in Transition: Trends and Reasons of Changes in Wage Inequality in the Hungarian Business Sector, 1986-2008

Abstract

Exploiting a large linked employer-employee dataset of 2.8 million observations on workers employed by 37,000 enterprises, I study earnings inequality of full-time employees in the Hungarian business sector. I find that the dispersion of real monthly earnings – as measured by several inequality indices – increased rapidly from 1989 to 2000, then declined significantly until 2002, started to rise again shortly, but returned to a decreasing path in 2005. At its peak level, wage inequality was the highest among OECD countries. Within-firm variance constantly declined throughout the period while all changes in total wage dispersion are reflected in between-firm variance. This is to some extent explained by differences in within-cohort variances of new entrant firms. Half of the decline between 2000 and 2002 is explained by a 57 per cent increase in the real value of the minimum wage. Between 2002 and 2008, when measures on working hours are available, I do not find any evidence of working hours explaining trends in inequality of monthly earnings. Results do not change significantly when controlling for the changing size criteria of sample inclusion for companies across years. The contribution of changes in skill composition is around 30%, mainly due to the increasing dominance of high-skilled workers in terms of growing employment shares, group-level inequality and mean wages. Yet, a large part of inequality changes remains unexplained by observable factors.

1.1. Introduction

Wage inequality got into the center of attention of labor economists in the late eighties, and the enthusiasm of researchers to understand the driving forces behind the evolution of wage and earnings dispersion has not dwindled in the last two decades. However, the focus of this enthusiasm was aimed mostly at the labor market of the United States and of developed countries. Transition economies remained out of the spotlight, partly due to the lack of large-scale databases that include individual observations on wages.[1] The low research output is especially regrettable since transition provides an ideal setting to investigate changes in the level and the structure of wages. In Central and Eastern European countries, wage determination became decentralized within a couple of years, the labor market and other factor markets turned more flexible and more open to international competition. Employers faced harder budget constraints, a tougher competitive environment, but at the same time easier access to liquidity and other resources. Employees had to deal with massive job destruction during early transition and changing skill requirements, but also found new opportunities of education and training.

Hungary stands out regarding the speed of transition and thus provides a particularly valuable terrain for the analysis of the wage structure. The country was ahead in the market liberalization and privatization processes, and it became in many dimensions – like openness of markets, degree of corruption, development of regulation, ownership structure and business environment – more similar to developed Western European economies than other countries in the region. Regarding the wage structure, Rutkowski (1996) shows that Hungary displayed the largest level of earnings inequality before the start of transition. In the light of this fact, it is even more remarkable that according to the OECD (2007), Hungary exhibited the largest growth in earnings inequality between 1994 and 2005, as measured by the change in the 90-10 interdecile ratio. In 2000, the difference between the 90th percentile and the 10th percentile worker of the wage distribution exceeded the difference measured in the United States.

[1] Noteworthy exceptions are Rutkowski (1996), Keane and Prasad (2006), Ganguli and Terrell (2006) and Kertesi and Köllő (2000).

Rising wage inequality is interesting in itself, but it also has farther-reaching implications. Milanovic (1999) found that in transition economies, the most important driving force behind the rise in overall income inequality was the rapid increase in the inequality of earnings. Moving from a long period of the common notion of pervasive income and earnings equality to such a high level of inequality within less than two decades makes people feel that these differences in the wage and income structure are "unjustified" and feeds a general disappointment with the transition process.

In this paper I analyze the extent of inequality growth of real monthly earnings in the Hungarian business sector over two decades between 1986 and 2008, using a large linked employer-employee dataset of 2.8 million observations on workers employed by 37,000 enterprises. Empirical evidence on overall Hungarian wage inequality is scarce and relates mostly to the early nineties. Éltető (1996), Pudney (1994) and Rutkowski (1996) all document a huge increase in earnings inequality during the early phase of transition, using different datasets. The most thorough analysis of inequality is provided by Kertesi and Köllő (1997), but their last year of observation is 1996.

In later years, there has been little attention paid to inequality indices, although some aspects of the wage structure were investigated. For example, Campos and Joliffe (2004) estimate the effects of market liberalization on the gender wage gap; Kertesi and Köllő study skill differentials (2002) and industrial wage differences (2003a, 2003b); Neumann (1997, 2002) explores the effect of collective wage bargaining; and Köllő and Nagy (1996) study the effects of unemployment on earnings. I show that earnings inequality continued to rise in the late nineties until 2000 – though at a smaller pace than in the first half of the decade –, declined significantly between 2000 and 2002, got close again to its 2000 peak level by 2005, and declined substantially in the last three years of the sample. Besides the time pattern of inequality changes, I also explore how different parts of the distribution were affected in a given period. I find that inequality above the median was on the rise constantly, while the dispersion among below-median employees declined, mainly due to an almost sixty percent increase in the real value of the minimum wage.

Low-skilled men lost the most in terms of real earnings and high-skilled women enjoyed the highest wage gains.

Most economists concerned with wage inequality tend to use a rather narrow set of inequality measures, typically interdecile differentials, the standard deviation (or variance) of log wages and the Gini coefficient. Beyond the fact that these measures do not fulfill some desirable properties, other measures – applied extensively in sociology and the income inequality research – may yield different results with respect to the direction and magnitude of earnings inequality changes. Studying the distribution of individual earnings in the United States between 1967 and 1986, Karoly (1992) demonstrated how, despite common general tendencies, various inequality indices imply different levels of inequality growth. In some cases, alternative measures even differ in how they rank yearly earnings distributions ordinally.

To check the robustness of inequality growth, I use a broad set of inequality measures that differ *inter alia* in their sensitivity to changes in certain parts of the earnings distribution. The results in this paper are in line with Karoly's findings: alternative measures produce up to three-fold differences regarding the magnitude of yearly inequality growth rates, and in some years, some indices display changes opposite in sign to what the majority of measures show. Nonetheless, the general pattern of inequality changes is reflected by all kinds of measures.

After describing patterns of inequality change, I investigate the "nature" of changes, that is, I am looking for possible reasons of rising or falling wage dispersion. Most of the analysis is not causal – or causal only when very stringent assumptions are met –, however, it provides insights about the suggested focus of research identifying causal determinants of the evolution of inequality.

In particular, first I construct hourly earnings measures for the years when the data allow me to do so (2002-2008), and confront results based on hourly earnings dispersion with results from monthly earnings distributions. I find that for the available years, inequality measures of hourly earnings are very close to what I get when working with monthly earnings.

The government increased the nominal value of the minimum wage in two steps, in 2001 and 2002, which resulted in an increase of the real minimum wage of 57 percent from 2000 to 2002.

I apply the method of DiNardo et al. (1996) to control for this change and to answer the counterfactual question: What would have happened to inequality in this period, had the minimum wage remained at its 2000 level? I find that although the minimum wage explains a large part of the change in inequality – especially below the median of the distribution – it explains by far not all of it. In particular, inequality in the bottom part of the distribution would have declined even in the absence of the minimum wage increase.

I also use DiNardo et al. (1996) reweighting to control for changes in the composition of the work force by constructing counterfactual inequality measures where skill distribution is held constant at its start-of-period level. Skill composition effects had an upward pressure on inequality throughout the sample period even in subperiods of decreasing inequality, but their relative importance varies over time.

Wage inequality within and between skill groups is also analyzed by a Shorrocks (1980) type of decomposition, where subgroups are defined either along highest levels of education, or according to experience levels. Changes in the composition of the work force concerning highest level of education had a positive impact both through increasing shares of high-inequality and high-wage groups, and through increasing divergence of group-level mean wages. Inequality levels within subgroups rather followed the general trend in overall inequality by also exhibiting some periods of decline.

While both within- and between-group inequality is an important factor in case of educational groups, for experience groups I do not find any evidence for between-group inequality to be substantial. Mean wages of different age groups are rather similar, although there are differences in group-level variation with prime-age groups displaying the largest level of inequality.

Finally I address an often neglected issue in wage inequality research, namely the role of firm composition. The results are quite striking as changes in overall inequality are only reflected in changes in between-firm inequality, while within-firm inequality is constantly decreasing from the outset of transition. A major motor for the huge inequality growth between 1989 and 2000 is the entry of a high-variance group of firms during the first half of the nineties. The most interesting direction suggested by the paper would be a deeper analysis of the determinants of differences in mean wages of firms, and the role of changes in the distribution of average wages across firms.

In the following section, I introduce the dataset used for the analysis, and explain how observations were weighted to account for different levels of representation of different worker groups. Section 3 gives a general overview on the evolution of wage inequality by using visual tools; commonly applied inequality measures in the wage inequality literature; and inequality measures borrowed from the income inequality literature. In Section 4, I investigate several aspects of changes in inequality over time, such as the role of working hours; the role of the minimum wage increase between 2000 and 2002; and the role of changes in the composition of firms and workers. Finally, Section 5 concludes and sets some directions for future research.

1.2. Data Sources and Sample Construction

The dataset used in this paper is the Hungarian Wage Survey (HWS), the most appropriate data source available in the country for wage dispersion analysis. The HWS is conducted at the level of firms, but its output is individual-level data on the employees of sampled companies. I also rely on firm-level data assembled by the Hungarian Tax Authority (HTA) when constructing sample weights and when defining cohorts of firms later in the paper. A short description of the weighting scheme and that of the HTA database follows later in this section.

The data host of the HWS is the National Employment Office, but data collection is carried out by the Central Statistical Office of Hungary (CSO). It is a matched employer-employee dataset, existing since 1986, containing yearly information on workers and establishments at the plant level. Although the survey was not executed in 1987, 1988, 1990 and 1991, the data still include two years prior to transition, which enables the researcher to address the question of how earnings inequality changed while the country was moving from a socialist to a capitalist regime. The last available wave used in this paper is 2008.

The HWS is based on a questionnaire filled out by a sample of Hungarian firms in May each year. Employers are requested to provide information on the size of their work force, on the number of blue- and white-collar workers, on their main activity (4-digit NACE code), and on several characteristics of a sample of their employees selected according to different sampling guidelines for blue-collar and white-collar workers. Additional information on the geographical area of the plants' location is supplemented by the CSO. [2] Until 2001, only data on full-time employees were collected, part-time workers should have joined the target population from the following year according to the description of the database. However, the first year in the data when workers actually classify as part-timers based on their reported regular working hours is 2003. I define part-time employees as workers with less than 35 reported regular hours a week and exclude them from the sample between 2003 and 2008, thus all results in the paper consistently refer to full-time employees only.

The sampling frameworks for both employers and employees have changed several times during the 1986-2008 period, affecting the size, coverage and consistency of the dataset. In 1986 and 1989, all firms of the Hungarian business sector were surveyed. In every year after 1992, all companies with more than 20 employees were included in the sample. From 1994, in addition, a random sample of a sub-population of smaller-sized firms was selected, where this sub-population covered employers with 11-20 employees between 1994 and 1999, and those with 5-20 employees for the period 2000-2008.

With respect to sampling of full-time workers, we can distinguish between three main regimes.[3] The first regime refers to the sampling practice before transition (i.e. to the years 1986 and 1989), the second covers the years 1992-1993, and the third captures the sampling procedure between 1994 and 2008. During the first regime, all senior managers were included. A random sample of the rest of white-collar workers was selected consisting of the first and then every fifth person of groups formed by workers of similar qualification and working conditions in 1986, and the first and every tenth employee in 1989.[4] In case of blue-collar workers, the survey covered the

[2] Regarding employer and geographical location information, only birth of the firm and the number of employees were used in this paper, the latter to construct weights, and to cut the sample at different size thresholds.
[3] Since this paper only deals with full-time employees, the sampling of part-timers is not described here in detail.
[4] Under the socialist regime, all employees were classified into so-called "tariff categories", based on qualification of the worker and working conditions of the job. Membership in the categories determined one's wage, hence the term "tariff".

first and then every seventh worker of each group in 1986, while the first and every tenth person in 1989.

In the three years of the second regime, every blue-collar worker born on the 5th or 15th of any month and every white-collar worker born on the 5th, 15th or 25th was included in the sample. This scheme was maintained during the third regime for firms above a certain size, however, all employees' information were required from sampled companies not exceeding that limit. The size threshold was 20 employees from 1994 to 2001, and it has been 50 employees since 2002. Foreign employees without a residence permit, pensioners working full-time, employees working abroad (except for a delegation), employees on loan and on exchange (*at* another firm or *from* another firm), and employees who were not receiving wage for more than three days in May were not sampled.

In order to account for the different degree of representation of the two occupational groups of employees within firm, I constructed weights for each group separately – called individual weights henceforth – as given by the ratio of the number of employees of either type on payroll in May and the actual number of workers observed in the sample.[5] Individual weights thus show how many individuals are represented by one observation within any given firm. The HWS contains a lot of mistakes regarding reported May employment, which were cleaned where possible using time-series information on the same variable and on average yearly number of employees as well. Whenever the construction of individual weights was impossible due to either missing data or to data errors, I used average individual weights of firms of similar size, or in some cases theoretical weights, that is, the inverse of the probability that a given employee was selected into the sample.

In addition to within-firm weights, to render the sample representative of the non-public sector of the economy, I am also applying company-level weights computed by dividing the total number of employees in arbitrarily defined size categories by the sum of individual weights within the corresponding size category. The figures on total employment by size are gained by adding up

[5] The weighting procedure relies heavily on the ideas of, and preliminary work done by researchers at the Institute of Economics of the Hungarian Academy of Sciences.

firm-level employment numbers found in the HTA database, which virtually contains every firm registered in Hungary that conducts double-entry bookkeeping for the years 1992-2008.[6] For 1986 and 1989, I used employment information from annual labor market statistics.[7] The final weight of each worker-year observation is then simply the product of the individual and the company weight, and it approximates the number of employees of the Hungarian business sector represented by a single worker in the sample.

The complete HWS dataset comprises 2,932,770 full-time worker-year observations, and a total of 38,499 unique firms that employ at least one full-time employee. However, there are several reasons to further restrict the sample. First, data files include firms also below the sampling size limits pointed out earlier in this section (21, 10 and 5 employees, depending on the period), and their size distribution rejects the possibility that they may have gotten into the sample randomly. Second, only implausibly few firms with less than 21 employees are observed in 1994 and 1995 – although a random sample of enterprises with 10 or more workers should be included according to sampling guidelines –, so I drop all firms below or at the twenty-employee threshold in these years. Third, I exclude workers with missing observations on wages, education, experience, gender, occupation, industry or region, which affects only a very small fraction of the data, about 0.004 percent. Finally, following ILO standards, I focus on individuals between the age of 15 and 74. At the end, I work with a sample of 2,826,044 individual observations on employees of 36,598 unique companies.

Both individual- and firm-level data were cleaned thoroughly by researchers and research assistants at the Institute of Economics of the Hungarian Academy of Sciences (IE-HAS) and at the CEU Labor Project. We managed to ensure to a great extent the continuity and consistency of the database. In addition to the aforementioned process of cleaning variables necessary for the construction of sample weights, extensive cleaning efforts were made to get rid of spurious

[6] One caveat here is that there is a discrepancy regarding number of employees between the two sources in that the HWS provides information on employment in May, while firms report their end-of-financial-year average statistical employment to the Tax Authority. Thus, a firm may fall into different categories when calculating the numerator and denominator of company weights. Nonetheless, the correlation between the two measures is very high, above 0.9.

[7] Information on employment by size categories does not exist prior to 1989, thus I assumed that the size distribution of employers remained unchanged through the pre-transition period and imputed total employment numbers for 1986 accordingly.

company exits and entries by detecting longitudinal linkages among exiting firms and new entrants in the consecutive year;[8] to harmonize several variables across years;[9] to fix "roundtripper" values (implausible back-and-forth changes within a few years); and to fill missing values where the imputation was plausible.[10]

Table 1.1 summarizes year-by-year information on the unweighted size of the sample, and on the number of workers and firms represented by the sample, conditional on individual and company weights. Except for the first two years, in each year the number of workers is between 83 and 140 thousand, making a random sample of 3,679 employers in 1986, 7,518 in 1997, and 7,639 in 2008. The sample represents a total employment of more than 3 million in pre-transition years, and of 1.7-2.1 million after transition. Note that the large increase in the number of represented firms is to some extent a consequence of changes in the sampling design already described earlier in this section. In order to account for these changes, I will also present results that rely on a consistent sample that includes only firms which have at least 20 employees in any given year.

The Wage Survey contains information on worker characteristics such as age, experience, highest education completed, gender, current occupation, and data on individual earnings in May[11]. Between 2002 and 2008, weekly regular hours and actual hours worked in May are also available; hence it is possible to construct two hourly earnings measures. For baseline measurements, however, I am using the broadest gross monthly earnings category that is consistently available for all years in the HWS, and which is defined as the sum of all payments to the employee in May at the expense of the employer's wage cost account, including base salary, allowances (for overtime, night shift, language proficiency, work abroad, etc.), regular monthly premia, bonuses and

[8] Spurious exit and entry are common to establishment-level datasets, and also present to a great extent in the Hungarian data. The cleaning procedure benefited first of all from a registry compiled by the CSO, which revealed valuable data until 2002 on boundary changes of companies, such as mergers, acquisitions, split-ups and spin-offs, and also provided information on spurious changes in continuing firms' identification numbers due to re-registration or bankruptcy, for example. In addition, we found longitudinal links in the data by matching exiting and entering firms by comparing their employment, settlement and industry codes, ownership and net sales revenue.

[9] In particular, pre-transition and post-transition industry codes were harmonized at the two-digit level to the common classification of TEAOR '92 (meaning the Hungarian industrial classification system, very close in nature to NACE); a consistent five-degree scale of highest degree of education was created; and we translated socialist occupational codes to post-transition codes that are consistent with Eurostat norms.

[10] For example, in industry code sequences of the form A . A, the missing value in the middle year was replaced with A. Also, missing information at the end or at the beginning of a firm's spell was replaced with the last or first known piece of information, respectively.

[11] The only exception is 1986, when the survey refers to September data.

commissions, and one-twelfth of total premia, bonuses, commissions and thirteenth-month salary passed in the previous year.[12] Since the personal income tax system was only introduced January 1, 1988 in Hungary, I grossed reported 1986 monthly earnings by using the 1988 income tax brackets to infer hypothetical gross earnings that correspond to observed net earnings in 1986. By measuring inequality in terms of gross earnings, the redistributive effects of personal income tax influencing the level of inequality are not taken into account, which is in line with the main goal of this paper being a documentation of earnings, and not income, dispersion.

Table 1.2 presents descriptive statistics of the sample for three selected years. Unconditional mean real earnings increased by forty percent between 1989 and 2008, while the unconditional standard deviation of wages multiplied by almost 2.5 times in the same period. The skill composition of the workforce has also changed dramatically during transition. The number of university and college graduates tripled, coupled with a constantly diminishing ratio of workers with only primary education. The number of employees with secondary education increased only during the nineties, but seems to have been stabilized by 2008. Interestingly, the distribution of potential labor market experience did not change at all over these two decades.

The occupational structure of the business sector moved a little towards a higher share of skilled jobs, but changes are not as spectacular as in the case of education. One exception is the group of managers, the share of which more than doubled from 1989 to 2008. Regarding changes in industry affiliation, one can observe a rapid shrinking of the agricultural sector and the parallel growth of trade, services and machines and equipment manufacturing. In the next section, I present trends in wage inequality without taking into account the changes outlined in Table 1.2, but in Section 4, I analyze how some dimensions of compositional changes affected the dispersion of wages.

[12] This term is a proxy for irregular bonuses and premia. Since these are irregular payments over the year, their monthly value can only be approximated by dividing last year’s total by twelve. If the worker was hired during the previous year, this item is transformed to be proportional to the number of months the worker spent with the company in the year of entry.

1.3. Trends in Wage Inequality

To get a broad though instructive picture on the evolution of earnings inequality in the last two decades in Hungary, Figure 1.1 presents estimates of kernel density functions for the distribution of log real gross monthly earnings in 1989, 2000 and 2008. The change in the shape of the wage distribution is remarkable. The pre-transition distribution exhibits a tightly compressed density function for both genders, which supports the general image of a non-competitive socialist labor market, and a centrally controlled wage-setting regime biased towards social equality leaving no or very little scope for individual companies and employees to negotiate wages. The shape of the wage distribution changes dramatically by 2000, as the density spreads in both directions. Also, the density function is censored at the minimum wage, marked by a vertical line. By 2008, this censoring happens at a much higher wage level, which seems to be disproportional compared to the overall shift of the whole density to the right. The shape of the 2008 distribution is very unusual in the sense that it has four modes. This is a consequence of the fact that the government introduced a multi-level minimum wage system in 2006, with a general national minimum wage and two "guaranteed wage minima" for skilled workers of different experience levels.

The minimum wage and monthly earnings are not directly comparable, since the latter include non-wage elements, like overtime pay, bonuses, premia, and so forth, but even so the minimum wage seems to play an important role in determining the shape of the earnings distribution. The institution of the minimum wage was already introduced in 1989, but its value was so low in real terms in the first few years that it was practically ineffective. From 1994 on, the wage distributions are two-modal, and following a significant rise in the real value of the minimum wage between 2000 and 2002, the minimum wage in fact becomes the highest frequency point of the density. I will discuss the role of the minimum wage increase in detail in the next section by constructing counterfactual densities that control for the change in the minimum wage between 2000 and 2002.[13]

[13] In Hungary, reporting minimum wages instead of true earnings is not uncommon. I will not deal with the effects of misreporting wages in this paper. For an instructive analysis of the issue see Elek et al. (2009, 2011).

In 2006, two guaranteed wage minima for skilled workers were introduced – in addition to the common minimum wage –; while from 2007, the minimum base for the payroll tax that employers had to pay after their employees was set to be the double of the minimum wage (or the guaranteed wage minimum). The minimum wage and the guaranteed wage minima in log terms were 11.14, 11.32 and 11.37, respectively; while the logarithms of the double of the wage minimum and guaranteed wage minima were 11.84, 12.02 and 12.06. Since the values related to the guaranteed wage minima are very close in log terms, these six numbers correspond to the four spikes in the 2008 density of earnings.

It is not straightforward to take away from Figure 1.1 – although an apparently bigger probability mass in the 2000 and 2008 female distributions to the right of the 1989 density is indicative – but the gap between male and female mean wages was narrowing since the start of transition. This trend is analogous to the findings of Campos and Joliffe (2004) that show that the gender wage difference in log wages declined from 0.31 to 0.19 between 1986 and 1998 in Hungary. It is also in line with other countries' experience in Central and Eastern Europe. Brainerd (2000), for example, documented a reduction in the gender wage gap during transition in Slovenia, the Czech Republic, Poland, Estonia, East Germany and Slovakia. Nonetheless, within-group inequality was on the rise in Hungary for both genders as demonstrated later in the paper. Note also the large difference between the earnings of men and women in 1989, which seems query the widely stressed socialist claim of gender equality on the labor market – however, one should be cautious to draw substantive conclusions from this unconditional wage gap.

As we saw, the evolution of the minimum wage determines to a great extent the shape of the wage distribution. Figure 1.2a and 1.2b follow changes in the log real value of the minimum wage along with changes in the mean of log real wages. Right at the beginning of the time series in Figure 1.2a, the evolution of the minimum wage departs from that of mean wages, since the latter drop by thirty percent by 1992, while the minimum wage does not lose from its real value due to an increase in nominal terms by the government. However, as mean wages increase while the minimum wage decreases in the following two years, the two curves get aligned in 1994 and evolve remarkably similarly until 2000.

The nominal value of the minimum wage was raised by almost 57 percent from 2000 to 2001 and by an additional 25 percent in the following year, which resulted in yearly increments of 44 percent and 19 percent in real terms, respectively. After 2002, the pattern of changes in the two series become quite similar again, but the discrepancy concerning the relative values of the two variables in terms of their own values in the base year remains there. It follows that while the real value of the minimum wage was 27 percent of mean real earnings in 1998, this ratio increased to 36 percent by 2008. I will analyze the role of the minimum wage increase in changes in wage inequality between 2000 and 2002 later in the paper.

Figure 1.3 plots the evolution of five selected points of the real earnings distribution in the pooled sample: the 90th, the 75th, the 25th, the 10th percentiles and the median. Transition caused wages to drop sharply – by twenty percent in six years – at all points of the wage distribution. With temporarily recovering wages, the spreading out of the distribution started in 1992. The stabilization package of 1995 again resulted in a serious fall in earnings that left the quantiles below the median at a lower wage level than the collapse of the socialist system in 1990.

The widening of the gap between low-wage and high-wage workers is remarkable. The 90th percentile employee enjoyed real wage gains in all but five years, with a particularly pronounced average growth rate of 4.6 percent per year following 1996. Real earnings at the 75th, the 50th and the 25th percentiles were increasing more slowly, at a decreasing pace moving from the top to the bottom of the distribution. Despite the pervasive increasing tendency from the second half of the nineties, even by 2006, nobody below the median earned more in real terms than the equivalent employee in the 1986 distribution, while workers at the two top quantiles gained 18 and 41 percent by the same time.

The first decile worker was hit hardest as in the worst year – in 2000 –, wages at this quantile were worth only 65 percent of their purchasing power in 1986. The surprising behavior of the 10th percentile between 2000 and 2002 is explained by the fact that the real minimum wage became the 10th percentile of the distribution. As a consequence of the huge increase in the legal minimum wage in both nominal and real terms described earlier, 13.2 percent of the employees in the sample earned not more than the minimum wage in 2002, whereas the figure was only 4.9 percent in 2000 (10.2 percent in 2001).[14]

In Figure 1.4a and 1.4b, I show how the changes in real earnings at selected percentiles translate to changes in earnings inequality above and below the median, respectively. With only a little halt in 1995, inequality in the top half of the wage distribution was increasing steadily for both genders until the last 3-4 years. For women, the trend turned in 2005, while for men one year later. The 90-75 and the 75-50 differentials follow very similar increasing paths until the last two years, when the 75-50 differential drops significantly to its 2002 level, while inequality among the very top earners decreases only slightly. The maximum difference between the 90th percentile male worker and the median worker in logs in 2006 translates into a 2.7 time difference in levels. The multiplier is only a bit lower, 2.6, for women. Investigating also changes in the bottom half of the distribution it is evident that total inequality was at the top not around 2005-2006 but in 2000, before the huge decline in the 50-10 log wage differential. In that year, the ratio of earnings at the 90th percentile to earnings at the tenth percentile reached 4.8 in case of women and 5.8 in case of men. Such a high level of inequality of earnings was unprecedented among OECD countries, and exceeded even that of the U.S.[15]

For both genders, inequality below the median drops sharply during the two-step minimum wage increase; then rises slowly again until 2006; and decreases further after, reaching its 1986 starting value. However, this pattern is only observable at the very bottom of the distribution, since the 50-25 differential is on the rise continuously – with the exception of the last two years – for men; and declines only slightly between 2000 and 2002, and after 2006, for women.

Figure 1.5 adds even more details to the analysis of changes in the wage distribution by displaying real wage changes across all percentiles in four periods: 1989-2000 and 2002-2005 –

[14] Without weighting the figures are somewhat higher, 13.4, 5.9 (and 12.8) percent, respectively.
[15] For a comparison of interdecile ratios of OECD countries, see OECD (2011). By 2008, Hungary had the highest level of 90-50 differential, and the fourth highest 90-10 ratio, topped only by Korea, Portugal and the U.S.

periods of increasing inequality (black markers); and 2000-2002 and 2005-2008 – periods of decreasing inequality (gray markers). Patterns for men and women are very similar except between 1989 and 2000, a period of a decreasing raw wage gap between men and women.

The first decade of transition is characterized by a remarkably pervasive inequality growth with a strongly monotone and above the eighth decile strongly convex relationship between wage change and position in the wage distribution. Roughly speaking, only women above the median and men in the top twenty percent gain in these years in terms of higher real earnings, those in the bottom half see their earned income decline, the least skilled by nearly twenty percent. Men around the first decile suffer the largest losses in real earnings of more than forty percent of the 1989 value. This monotone relationship is very similar to what Juhn, Murphy and Pierce (1993) find regarding changes in real weekly wages in the late 1970s and in the 1980s in the United States, with the difference that wage changes in the U.S. labor market were almost perfectly linear and increasing across percentiles.[16]

As pointed out earlier, the years between 2000 and 2002 are special in the sense that inequality changes seem to be driven by the minimum wage. For percentiles which already earned the minimum wage in 2000, the 71 percent increase in the real value of the minimum wage obviously translates directly into measured real earnings changes as apparent from the upper row panels of Figure 1.5. However, also the above average growth rates of the bottom twenty-thirty percent of both distributions can be explained by the fact that these employees either earned the minimum wage in 2002 that was way higher in real terms than what they had earned in 2000; or the huge increase in the minimum wage probably pushed up wages at close percentiles also. This latter mechanism was presumably stronger for women, since their wage change profile becomes flat only after the 40^{th}, while for men after the 25^{th} percentile.

In the three years that follow, we again observe linear profiles for both genders – similar to early transition patterns –, with somewhat higher wage growth for men. The benefits of the

[16] The relationship was indeed linear in Hungary for the very first years of transition. This is consistent with also what Kertesi and Köllő (1997) report using the same data and the same earnings variable.

minimum wage increase get inflated away, [17] moreover, the whole first quartile displays close to zero or slight negative growth rates. Nonetheless, the top 75 percent of both distributions enjoy wage gains up to twenty percent. A possible explanation for this phenomenon may be the return of the labor market to the wage differentials that prevailed before the minimum wage increase. As the real value of the minimum wage rises, wage differentials between minimum wage and non-minimum wage jobs narrow, hence, all things being equal, wages have to grow in order to get back to the old premia paid due to higher skills, compensating differentials, discrimination, efficiency incentives, union pressure, etc. Since wage difference between jobs closer to each other in the distribution are more visible to both employers and employees, the increase in minimum wage may first push wages in the bottom end higher, and then the effect triggers a chain reaction up the distribution.

Finally, the last years of the sample are very interesting since trends turn and inequality starts to decline for all but the lowest 15 percentiles. This is approximately the share of workers at or below the minimum wage in 2005, which drops to 4.4 percent in case of women and to 2.8 percent in case of men by 2008.

If we pool plotted wage changes against percentiles for the period 1992-2005, and add wage changes between 1986 and 1992, we get a graph that is in many aspects very similar to Figure 1.4 in Lemieux (2007), which illustrates changes in the real hourly wages of men by percentile on May/ORG CPS data. Lemieux divides the thirty years between 1974 and 2004 into two periods of equal length. In the second half of the 1970s and in the 1980s, the growth in inequality was pervasive, meaning that the higher we move along the percentiles of the distribution the larger/the less negative is the growth rate of wages; moreover, the relationship was linear (except for the upmost eight percent, where it was convex). In stark contrast, during the nineties and after the turn of the century, the curve of wage growth plotted against location in the distribution became U-shaped. Workers between the twentieth and fiftieth percentiles experienced the smallest gains, and

[17] In 2005, 12.1 percent of women and 12.6 percent of men earned at most the minimum wage.

were outpaced by both upper-tail and lower-tail workers (with the highest increase in the top fifteen percent).

Figure 1.6 in this study tells a similar story for Hungary, but with differences in the magnitudes, the time horizon, and the motors behind changes. The linear pattern is present in the first years of transition, and wage changes range between -31 and 8 percent (for the U.S., these numbers are -20 and 12) within a time span of only six years. The interception with the zero line is at the 96th percentile, not at 79th, as on the graph of Lemieux. We can also see a pronounced U-shaped curve in the 1992-2005 period, which is even more asymmetric than the CPS counterpart with workers at the bottom reaching earnings growth rates of more than thirty percent, while those at the top enjoying twice that pace. The interval of the "worst" percentiles is slightly shifted to the left compared to the U.S. graph, since employees between the tenth and thirty-fifth percentiles have to settle with earnings losses, while at all other parts of the distribution we see positive differentials. The major difference is that while polarization is mostly due to demand factors and changes in unionization in the U.S.;[18] in Hungary, the downward sloping left tail of the curve seems to be a direct consequence of the minimum wage increase.

So far, I have only analyzed interquantile differences, but often we would like to characterize wage distributions with one inequality index. The reason for this might be policy-oriented: policy makers are often interested in a yes/no type of question whether inequality increased (decreased) or not. But more importantly, a certain class of inequality indices widely used foremost in the income inequality literature has some desirable properties that interquantile ranges do not.

The problem of measuring inequality with a single index is that different indices might rank wage distributions differently at a given point in time, and also, they might give different answers to the question of how inequality changed over time. It can be shown that it is only possible to rank two distributions unambiguously according to dispersion, if the corresponding Lorenz-curves do not intersect. That is, the one that lies closer at all points on the axis of cumulative frequencies to

[18] See Lemieux (2007) and Autor, Katz and Kearney (2006, 2008).

the 45-degree-line (representing perfect equality) exhibits lower inequality by all possible measures.[19] If, however, the Lorenz-curves do intersect – and this is what we see most often in real data –, we can always find two inequality measures that will rank two distributions differently in ordinal terms.

Using CPS data, Karoly (1992) has shown empirically that different measures yield different implications regarding the magnitude and even the direction of changes in wage inequality in the United States from 1967 to 1986. Of course, it is always to a great extent a subjective decision which inequality measures the researcher might want to apply, since different measures possess different properties with respect to how they respond to transfers between different points of the distribution.

The 90-10 gap, for example, is not affected by any earnings changes in the middle part of the distribution, as long as these do not influence the value of the tenth and the ninetieth percentiles. Also, the 90-10 differential may record a huge growth in wage inequality if its two components get further away over time, even if accompanied by equalizing redistributive processes around the mean which might cause other measures to document a more moderate growth rate, or even a decline. Thus, once we know the sensitivity properties of these measures, we are able to infer what parts of the distribution contributed most to the general inequality trends.

It is common in the income inequality literature to *ex ante* postulate some desirable properties of inequality measures. Cowell (1977) lists three principles that may help to reduce the set of possible choices. First, an inequality measure should be independent of scale, that is, if everybody in the population earns a scalar multiple of what he or she earned in the previous period, then measured dispersion should not change.[20] Second, an inequality measure should satisfy the principle of population: If the population is merged with an identical one, measured inequality should remain the same. Finally, a desirable property may be the weak principle of transfers which states that as a consequence of a mean-preserving positive transfer from a higher to a lower part of

[19] See Atkinson [1970], Cowell [1977]
[20] This principle is also called mean independence in the literature.

the distribution (in a way that the recipient does not become better-off than the donor) inequality should decrease.[21]

Concerning the most frequently used measures, the standard deviation (of levels) fails the first two principles, while the standard deviation of logs satisfies both, but fails the weak principle of transfers. The 90-10 measure is independent of scale and of replicating the population, but just fails the principle of transfers. "Just fails" means that it *may not* decrease following a transfer specified in the previous paragraph. (It will never record any change unless one of the participants of the transfer is at the tenth or ninetieth percentile of the distribution.) The Gini passes all the above tests, and is very sensitive to transfers around the mode of the distribution.

The group of inequality measures that satisfy all the above requirements, plus that are additively decomposable by subgroups into inequality within the subgroups and between the subgroups, is the general entropy class.[22] Member indices of the class are of the form:

(1) $$I_s(\mathbf{w}) = \frac{1}{n}\frac{1}{s(s-1)}\sum_{i=1}^{n}\left[\left(\frac{w_i}{\mu}\right)^s - 1\right], \qquad \text{if } s \neq 0{,}1,$$

$$I_0(\mathbf{w}) = \frac{1}{n}\sum_{i=1}^{n} log\,\frac{\mu}{w_i}, \qquad \text{if } s = 0,$$

$$I_1(\mathbf{w}) = \frac{1}{n}\sum_{i=1}^{n}\frac{w_i}{\mu} log\,\frac{w_i}{\mu}, \qquad \text{if } s = 1,$$

where $I_s(\mathbf{w})$ is an inequality index with sensitivity parameter s that might take on negative values as well, and $\mathbf{w} = (w_1, w_2, \dots, w_n)$ is a vector of wages for a population of n workers with mean wage μ. As s increases, the measure becomes more sensitive to changes in the top part of the distribution. That is, for a higher s, larger and larger transfers are required in the bottom to compensate for transfers in the top for inequality not to increase.

[21] The last principle is static in the sense that it assumes constant total income in the two periods that is simply redistributed. A dynamic interpretation would involve a skilled and a less-skilled worker, both of them enjoying (additive) wage gains from one period to the next, but the increase for the less skilled is higher. Other things being equal, this should result in a drop in inequality. Karoly (1992) mentions an even stronger version of this idea, the principle of equal additions, which, unlike independence of scale, concerns disproportionate simultaneous changes in everybody's earnings: If every member of the population earns by a constant amount more than before, then measured inequality should fall. Note that the principle of equal additions does not imply the principle of transfers.

[22] Shorrocks (1980) gives a detailed and rigorous derivation of the class. I will use the decomposability property later in the paper.

Figure 1.7a compares the evolution of the most commonly used measures in the wage inequality literature: the Gini coefficient (GINI), the standard deviation of logarithms (SDL), and the log 90-10 interdecile differential. Figure 1.7b collects some measures of the general entropy class, namely the mean logarithmic deviation (also known as Theil's entropy measure) with $s = 0$ (MLD), the Theil index with $s = 1$ (THEIL),[23] and twice the square of the coefficient of variation with $s = 2$ (CVsq).

In general, the message of alternative inequality measures is very similar to that displayed by the 90-10 differential: Inequality was growing from 1989 to 2000 – with a short break in 1995 –, then it declined sharply until 2002, but was on an increasing path again until 2005/2006 and diminishing afterwards. However, after closer inspection, there are some years when we find differences not only in the magnitude, but also in the direction of changes. First, consider the ordinal ranking of yearly earnings distributions by the various inequality measures. There are two measures that in some years point into different directions than the others, the coefficient of variation and the Theil index. Mostly, this is related to the male distribution, in years following the rise in the minimum wage. The Theil index and the square of the CV start to rise already in 2002, while other measures still exhibit a decline. This suggests that "redistribution" of wages in the upper end of the distribution resulted in greater inequality, but it was not captured by measures that are not particularly sensitive to such processes, and were probably "overloaded" by the minimum wage increase that compressed the bottom part of the distribution.

Commonly used indices in the wage inequality literature in general follow closely each other, with the exception of the Gini coefficient after 2001, which shows a higher level of inequality than the SDL and the 90-10 differential.[24] The Gini is particularly sensitive to transfers around the mode of the distribution, but in case of a two- and later four-modal distribution it is really hard to draw any substantive conclusions. The ranking among members of the general entropy class is indicative of the fact that wage inequality growth in Hungary is more driven by a

[23] See Theil (1967).

[24] It is important to note that the figures plot the evolution of the log 90-10 differential. The 90/10 ratio of levels of wages displays a much higher variation over time, in fact higher than any of the other measures, since all the other involve some transformation of the levels that compresses the underlying distribution.

top-end growth in dispersion rather than in the bottom. It is also worth to note that the CV is very volatile as a measure of inequality.[25]

1.4. Determinants of Inequality Changes

1.4.1. Working Hours

Up to this point, I have analyzed the distribution of real monthly earnings. Since it is possible that workers who earn more over the month also work more hours, real hourly wages would be the appropriate variable to measure "pure" wage inequality that is not affected by the distribution of working hours. Unfortunately, the HWS only provides information on hourly wages for a small subset of workers, namely those who contracted on hourly wages and not on a monthly salary – a very small fraction of the Hungarian workforce. Nonetheless, I am able to construct two proxies by dividing monthly earnings by measures of working hours. From 2002, the HWS contains two variables on working hours, both reported by the employer: the first captures reported weekly regular working hours; while the second counts hours actually paid in the month of the survey.

Figure 1.8 displays the evolution of log interdecile differentials computed on the distribution of monthly earnings and the two hourly earnings measure introduced above. Inequality in the top part of the distribution is almost exactly the same, no matter which measure of wages we consider. The absolute difference between the 90-50 differential measured by monthly earnings and by the respective hourly earnings measure is less than one percent in every year. We can only observe some deviation of the actual-paid-hours-based measure from the evolution of the other two variables between 2002 and 2005. Yearly values of this variable are lower on average by 3.7 percent in case of women and by 3.5 percent in case of men. These differences are still very minor, but if anything, we might conclude that inequality of monthly earnings below the median is to some extent explained by high-wage workers working many hours and low-wage workers working less.

[25] Too big positive or too negative values of *s* render the behavior of indices in the general entropy class "strange", as Shorrocks (1980) notes.

About one third of the above difference carries over to the 90-10 differential, that is, the paid-hour-based proxy for the dispersion of real hourly earnings in the entire population is by one percent lower on average than the dispersion of monthly earnings.

Since interdecile differentials are independent of scale, if the majority of full-time workers report similar weekly regular hours, than dividing monthly earnings by this measure should not introduce large changes into measured dispersion. According to the evidence in Figure 1.8, this seems to be the case. Actually paid working hours do not make a much more spectacular difference either, so at least in this period, there is no evidence of changes in hours worked being a major explanatory factor of changes in inequality of monthly wages.

1.4.2. The Effect of the Minimum Wage Increase between 2000 and 2002

In this section, I am interested in the question: How would inequality have changed, had the minimum wage not been raised between 2000 and 2002? The legal minimum wage probably has an effect also in other years on the wage distribution, but as we saw in Figure 1.2a and 1.2b, in other periods, the minimum wage moved in line with mean wages. Hence I will suppose that for other points in time, the role of the minimum wage in shaping the evolution of inequality is negligible and will only investigate differences between these two years.

To answer the main question of the previous paragraph, one has to construct the counterfactual density of wages in 2002 that would have prevailed, if the minimum wage had remained at its 2000 value in real terms. I rely on the method developed by DiNardo et al. (1996) to accomplish this task.[26]

The authors first construct counterfactual conditional densities, and then integrate over the distribution of individual characteristics to get the marginal (unconditional) distribution of wages. To obtain counterfactual densities, DiNardo et al. set three assumptions, which I will also apply. First, they presume that the minimum wage has no spillover effects on the distribution above the minimum wage (in the year of the higher level of minimum wage, i.e. in 2002). The visual

[26] An alternative would be to let the minimum wage change between the two years, for example, by the growth rate of mean real wages. However, in this paper I stick to the original setup in DiNardo et al. (1996).

evidence in Figure 1.5 suggested that this is probably not fully satisfied in the data, since there seems to be a spillover effect up to the 25th percentile in the male distribution and up to the 35th percentile in the female distribution. Thus, the results I will present probably underestimate the effect of the minimum wage increase on inequality.

Second, they assume that the shape of the conditional density at or below the minimum wage depends only on the real value of the minimum wage.[27] In other words, at or below the higher minimum wage, the counterfactual conditional density for the year with the higher minimum wage (2005) is proportional to the part of the conditional density at or below the higher minimum wage in the year of the lower minimum wage (2000).

Finally, DiNardo et al. postulate no effects of the minimum wage on employment probabilities. This is indeed a strong assumption as rising wages may lower the demand for certain workers. In the Hungarian context, Kertesi and Köllő (2004) estimated the disemployment effects of the minimum wage increase in 2001, and found that it had a negative effect of 3.5 percent on employment among firms with 5-20 employees. Although this is non-negligible effect, I will consider it not to bias the results seriously since I am interested in inequality in the whole distribution, and we will see in Section 4.3 that excluding this group of firms does not alter much the main results.

Accepting these assumptions, the counterfactual conditional density of wages in 2002 of workers with a given vector of individual characteristics is simply the actual 2002 density above the real value of the 2002 minimum wage, plus the density of wages of a reweighted sample below the 2002 minimum wage. The reweighting function equals the ratio of the probability of having a wage lower than the 2002 minimum wage in 2002 and the probability of falling below the 2002 value of the minimum wage in 2000 (conditional on the vector of individual characteristics) which can be estimated by a simple probit regression.[28]

[27] Note that the weighted ratio of workers with wages strictly below the minimum wage is only one percent in both years.
[28] Please find the formal details of these derivations in DiNardo et al. (1996).

By integrating the counterfactual conditional densities over the distribution of individual characteristics, we get a similar formula for the counterfactual marginal density of wages, only with a different reweighting function. Above the 2002 minimum wage, it is equal to the actual 2002 density, while below the 2002 minimum wage it is a reweighted version of the actual 2002 density. The reweighting function is now the ratio from the previous paragraph multiplied by the ratio of employment in 2000 and 2002. So basically what happens is that the probability mass at the 2002 minimum wage in the 2002 density is distributed proportionally based on the shape of the density in 2000 below the 2002 minimum wage and on the relative distribution of individual characteristics in the two years.

The actual densities and the counterfactual 2002 density are depicted in Figure 1.9. The dashed line shows the counterfactual density, which coincides above the 2002 minimum wage with the black solid line marking the actual 2002 density by construction. The mass at the 2002 minimum wage is transformed into a counterfactual left tail that follows the shape of the 2000 density. Note that for both genders, the probability mass in the counterfactual distribution below the 2002 minimum wage is smaller than the corresponding probability mass in the 2000 distribution, and the whole distribution is shifted to the right. Also, there remains a mass in the 2002 distribution just above the 2002 value of the minimum wage that is not transformed, and which might be the result of spillover effects as discussed earlier.[29] The mass is larger for women which is consistent with wage change patterns in Figure 1.5.

In Table 1.3, I quantify the effect of the minimum wage increase by comparing actual changes in inequality measures (first column) and the difference between the actual 2000 distribution and the counterfactual (reweighted) 2002 distribution (second column). The third column reports the share explained by the minimum wage of the actual change in a given inequality index in percentages.

The signs behind the numbers show whether the changes caused by the minimum wage point in the same direction as the actual change. A plus sign means they do, while a minus sign

[29] Remember from Figure 5 that in this period, the profile of wage changes is completely flat for percentiles that are sufficiently far from the minimum wage.

indicates effects of the opposite direction. For example, looking at the first row of the panel for women, we find that inequality changes caused by the minimum wage increase point in the same direction as the actually observed declining tendency in inequality. In other words, the drop in the 90-10 differential would have been smaller, had the minimum wage remained at its 2000 level. About half of the decline is due to the rise in the minimum wage.

For women, the minimum wage regulation contributed to a greater extent to decreasing wage dispersion. The more sensitive the measures are to changes in the lower part of the distribution, the larger the share explained by the minimum wage change. Inequality in the top half of the distribution grew with and without taking into account the differences in the minimum wage. Finally, it is important to note that although the minimum wage explains a remarkable part of the fall in inequality between 2000 and 2002, but neither does it explain all of it, nor does this method provide evidence for inequality to grow or even to stagnate without the presence of a higher minimum wage in 2002.

1.4.3. Composition of Firms

As a consequence of the sampling design outlined in Section 2, inequality is not directly comparable across years in the sense that the employment threshold of sample inclusion was changing, and firms with less than 21 employees are not represented in each year. Figure 1.10 charts results on a sample that only includes enterprises which employ more than twenty workers in a given year. Note that we expect differences only beginning with 1996, since the HWS contains no plausible information on companies with less than 21 employees in earlier years anyway.

Generally speaking, for both genders, the pattern of inequality changes is very similar to that computed on the full sample. In case of the 90-50 differential, inequality in the restricted sample is lower in all years, while for the 50-10 differential it is slightly lower before 2002 and higher after. One remarkable difference is observed for the bottom half of the male distribution, where the peak in the 50-10 gap is lower by around fifteen percent among large enterprises, thus, some of the growth in male wage inequality below the median until 2000 is due to a higher level of inequality among small firms. The end-of-the-period positive difference between the 50-10 measure in the restricted sample and in the full sample suggests that wage dispersion for the below-median fifty percent of workers declined after 2002 for firms with not more than twenty employees.

To consider another aspect of sample consistency and firm composition, Figure 1.11 compares histories for the same two measures, this time restricting the sample to companies which answered the HWS in at least 17 years. This means that all "old" firms (i.e. those which existed prior to transition) followed for at least 15 years after transition, and all "new" enterprises (i.e. those which are observed only after 1990) with a complete spell are included. After changes in firm composition are ruled out in this very crude way, the picture is very different from what we got in the full sample, especially in case of males.

Inequality above the median of the male distribution is still following an upward trend, yet with a much less steeper slope. The highest level of the 90-50 interquantile difference is 79 log points while in the full sample it reaches almost 100. Moreover, the highest point in the former case is reached in 2008, while in 2006 for the latter, which shows that the decline in inequality in the last 3-4 years observed in the full data is not valid for this type of firms. The evolution of the 50-10 differential is even more striking since the curve for the restricted sample is almost completely flat; in particular, there is nothing to be seen of the inequality attenuating effect of the minimum wage. This suggests that either inequality in the lower half of the male distribution is mainly a between-firm phenomenon, or that the oldest group of firms is a very selected and special group that differs from other types of businesses. I will find some evidence for both possibilities.

For females, the full-sample patterns are to some extent recognizable but there are major differences here, too. After 1992, the 90-50 differential is by 12 log points smaller on average, which is considerable concerning that the average rate of the differential in the full sample is 83 log points. Regarding differences between the fifth and the first decile, the effect of the minimum wage increase is smoothed out and seems to only modestly influence the wage distribution of these firms, as a consequence of which inequality of women below the median remains higher after 2002 in the continuing firms than in others.

To further address the issue of within- and between-firm inequality, Figure 1.12 displays the results of a standard decomposition of total variance of log wages into a within-firm and a between-firm component. While during the last years of socialism, inequality was almost completely a within-firm phenomenon, with the introduction of market mechanisms in wage determination, the share of between-firm variation increased to explain close to sixty percent of total variation in wages by the end of the period. Moreover, while wage dispersion within firms is basically falling constantly as time passes; between-firm variation follows very closely the evolution of overall inequality that we saw on previous graphs. The huge growth in inequality of the nineties or the large minimum wage increase did not seem to have any remarkable effect on within-firm inequality.

Figure 1.12 suggests that any analysis investigating changes in inequality should probably involve an explicit firm-level dimension besides the usual focus on individual factors, and address the role of firm-level heterogeneity. Of course, this does not mean that the within-firm dimension is unimportant since it explains still a significant share of the *level* of wage inequality, but that its role in Hungary is diminishing over time and that *changes* in inequality can be explained by factors that affect the variation in mean wages of firms.

One caveat related to within-firm analysis on these data is that the estimation of within-firm variance might get very noisy in case of firms for which very few employees are observed. This is the reason why I dispensed with splitting the sample by gender for this analysis. I also repeated the variance decomposition exercise of Figure 1.12 on a sample that only included firms with at least 10 observed workers, but results do not change qualitatively.[30]

Because firm composition is such an important aspect of wage dispersion in transition, I analyze in detail one dimension of it, the role of new entrants over time by distinguishing several cohorts of firms. I am able to tell the time of entry for each firm using the comprehensive firm-level dataset of the HTA, and merge this information to the Wage Survey through common firm identifiers. One main drawback of the HWS is that since micro enterprises are not surveyed, the

[30] For a sample of firms with at least 50 observed workers, the bars representing within-firm inequality are practically of the same size throughout the sample period (at a variance of 0.2), while between-firm inequality is constantly increasing with just a little drop during the minimum wage increase and in the last year (reaching a variance of 0.2 by 2007).

representation of newborn companies is so low that it makes their analysis impossible in their first years of existence. For this reason I pool years of entry and consider firms that were born within a five-year interval as one cohort. I group the data into cohorts of businesses started before transition, between 1990 and 1994, between 1995 and 1999, and between 2000 and 2004.

Having constructed these cohorts, I plot within-cohort variances of earnings (Figure 1.13a), cohort-level mean wages (Figure 1.13b) and the number of workers employed by firms belonging to the respective cohorts (both figures). I follow variances and means in both real and event time. For the former, the starting years of measurement are 1990, 1995, 2000 and 2005 for the cohorts described in the previous paragraph, respectively. In the event time framework, I consider these starting dates as year one for a given cohort, and plot the evolution of the moments of the wage distribution accordingly. 1990 should be the first year when I start to follow the pre-transition cohort, but since years 1990 and 1991 are missing in the HWS, real-time graphs start with 1992, while event-time graphs start with year three for this group.

Investigating first the evolution of workers employed, we see that employment in the pre-transition cohort declines steadily, and by 2008 it reaches only less than one-third of its value at the outset of transition. Nonetheless, it remains the largest sector even by the end of the sample period. The second largest employer, the cohort of 1990-1994 exhibits an increasing tendency until 2001, but starts to shrink immediately after, and by 2008, it employs the same number of workers as in 1995. This pattern is to some extent observable for the 1995-1999 cohort which displays an increasing employment for four years, then stagnates, and then starts to lose workers from 2006. The 2000-2004 cohort has a too short time series to talk about tendencies, but the magnitude of employment compares to that of other cohorts.

Turning to within-cohort wage dispersion in Figure 1.13a, it is clearly visible that the cohort with the highest variance is the group of firms that started operating between 1990 and 1994. Also, these companies display the highest volatility in earnings inequality together with the cohort of the second half of the nineties. These two groups are heavily affected by the minimum wage changes of 2000-2002, with inequality decreasing about twice as much as in the pre-transition cohort. Note that the decline in inequality in the last three years of the data is observed within cohorts as well, in all but the pre-transition cohort.

The story in Figure 1.13b is much simpler, since except for 1995-1997 (i.e. the years immediately after the stabilization package), mean real wages are on the rise in every cohort. It is very interesting to see, that wages paid by employers close to their entry are quite similar. Since wages are growing at the same speed for all cohorts there is no crossing of trends, that is, there is a hierarchy regarding average wages: firms that arrived earlier employ a higher paid workforce.

To sum up, the cohort of the early nineties contributed to a large extent to the fast-paced inequality increase of the decade, while for other periods it is less clear how this type of separation of the population of firms might explain trends in wage inequality. In particular, at the level of this aggregation, there are no notable differences in mean wages. As we saw earlier, the between-firm dimension is important, but as the high within-cohort variances show, it is important at a more micro level.

1.4.4. Composition of Workers

So far, except for the analysis in section 4.2, I computed inequality measures with actual sample weights, and for yearly earnings distributions resulting from the actual skill composition of workers. However, during transition, the composition of the work force changed substantially. During the early years of the transition process, many workers dropped out of the labor market – many of them for good – due to inability to adjust their skills to changing market conditions and due to bad incentives (e.g. flawed unemployment insurance and social policies). Kertesi and Köllő (1997) estimated individual job loss probabilities for the years 1986-1996 based on the 1993 Labor Force Survey to approximate the selection bias in earnings inequality. Their results show that over this period, the distribution of job loss propensities among employed people shifted towards workers with low transition probabilities to unemployment.

Köllő (2005) also showed that most workers who lost their jobs during this time became permanently inactive afterwards. Other workers managed to update their skills during a temporary state of inactivity by taking part in education and training, which also affected composition from two sides: by the transitory inactivity and by changing the educational composition after returning to the labor market. As demonstrated in Table 1.2, the ratio of workers with finished secondary and tertiary education, and the ratio of jobs with higher skill content increased during the sample period, while somewhat surprisingly the ratio of females and the average work experience of the workforce remained essentially the same.

In this section, I first decompose the Theil index according to the method of Shorrocks (1980), to see how inequality evolved between and within different groups of workers. Then I apply the reweighting method in Lemieux (2006) – originally proposed by DiNardo et al. (1996) – to construct counterfactual distributions of wages that control for changes in observable worker characteristics. Finally, I check to what extent composition effects, price effects and unobserved residual effects account for changes in wage inequality over time by running Juhn-Murphy-Pierce (JMP) decompositions (Juhn et al. 1993).

1.4.4.1. Shorrocks decomposition

Shorrocks (1980) derives a class of inequality measures that can be decomposed into within- and between-group inequality by subgroups of the population. This is the general entropy class which I introduced in Section 3. Of the class, I chose the Theil index (with sensitivity parameter one) because it does not place any particularly strong relative weight to either part of the distribution. I divided the sample into G disjoint groups by education on the one hand and by experience levels on the other, and decomposed the overall Theil index accordingly. The decomposition of the index can be written as:

(2) $$I_1(\mathbf{w}) = \frac{1}{n}\sum_{i=1}^{n}\frac{w_i}{\mu}log\frac{w_i}{\mu} = I_1(\mathbf{w_1}, \mathbf{w_2}, \dots, \mathbf{w_G}) =$$

$$= \sum_{g=1}^{G}\frac{n_g}{n}I_1(\mathbf{w_g}) + \sum_{i=1}^{n}\frac{n_g}{n}\frac{\mu_g}{\mu}log\frac{\mu_g}{\mu},$$

where $\mathbf{w_g} = (w_1, w_2, \dots, w_g)$ is a vector of wages in subgroup g of n_g workers with group-level inequality $I_1(\mathbf{w_g})$ and group-level mean wage μ_g. The first term in the sum in (2) is a measure of within-group inequality, while the second term measures inequality of group-level mean wages (between-group inequality).

For both the decomposition by groups of highest level of education and by experience groups, I set $\mathrm{G} = 4$. In the former case I distinguish workers with elementary education, with vocational education, with a high school degree and individuals with a college/university degree. In the latter exercise, I divide the sample of workers into a group with not more than five years of experience, a group with 6 to 15 years of experience, a group with 16 to 30 years of experience and a group with more than 30 years of experience.

Inequality within and between educational groups is depicted in Figure 1.14a. From 1989 to 2000, within-group inequality doubled while between-group inequality quadrupled for both genders. For men, both levels and growth rates are higher by all means. Both components follow the general pattern of inequality changes in the whole distribution: they increase for 1989-2000 and 2002-2005, and decrease for 2000-2002 and 2005-2008.

Figure 1.14b demonstrates how changes in group-level inequality and changes in the employment shares of groups contribute to changes in the within-group inequality component, and through that to changes in total inequality. The share of workers with only elementary education shrinks continuously, more so for men than for women. At the same time, the share of college/university graduates increases, reaching four times its starting value by 2008. This trend is basically the same for the two genders, both in direction and in magnitude.

There are between gender differences in the relative share of high school graduates and workers with vocational training, the former is larger women, the latter for men. Both groups increase their shares from 1989 to 2000, but these basically remain unchanged afterwards. Not all group-level variances follow the general path of inequality changes, e.g. inequality among female college graduates is decreasing constantly from 2000. Group-level inequality levels start from very similar magnitudes at the end of the socialist system, but diverge quickly afterwards, mainly because inequality of workers with tertiary education doubles. Inequality of subgroups is higher by all means for men, especially in case of college/university graduates.

Considering group-level mean wages, university and college graduates are the winners of transition with continuously rising mean wages. For men, the growth is more than 50 percent in real terms. After a decline from 1989 to 2000, other groups also see their earnings grow on average, but for the two least skilled groups, this hardly compensates for early-transition losses. Note also that unconditionally, mean wages of male college graduates are higher by almost thirty percent by the end of the period than that of female graduates.

To sum up, we can conclude that changes in the composition of work force by education contributed to rising inequality at all ends: by increasing group-level dispersion (except for some groups in some periods), by increasing differences in mean wages of workers with different education levels, and by increasing shares of groups with higher inequality and higher mean wages.

There is a stark contrast regarding the evolution of within- and between-group inequality by experience subgroups. Figure 1.15a provides evidence that for this division of experience levels, differences in group-level means only have a negligible contribution to total inequality, and all variation of wages is within experience groups. This is reinforced by the evolution of group-level mean wages in Figure 1.15c. All means move very close together and do not differ much from country-level average earnings (not shown in the graph). Nonetheless, prime age groups are the best paid workers, and the group with 16-30 years of experience is the only one that does not suffer a fall in real average wages from 1989 to 2000.

Turning to group-level inequality in Figure 1.15b, there is a larger variation between groups, but it only changes substantially over time for men. The most striking feature of inequality changes by experience group is that the reversed ranking of groups at the end of socialism (i.e. that older age groups had lower inequality levels) turns completely by 2000. By the end of the sample period, prime age groups have the highest level of inequality followed first by the most experienced and finally by the least experienced group. In general, all curves reflect patterns of inequality changes in the whole population, except for the very young, for whom inequality of wages is declining constantly from 2000.

The distribution of work experience changes by far less than the educational composition of the work force. The biggest change occurs between 1989 and 2000, when shares of the youngest two groups increase at the cost of the oldest group. However, the share of this latter group has been increasing ever since then with a declining share of the 16-30 prime age group. Whether this is a consequence of population aging only, or also of changes in some other dimensions in labor market participation and labor demand, is not possible to answer without further investigation that is beyond the scope of this paper.

1.4.4.2. DFL reweighting

In this subsection I use the reweighting scheme in Lemieux (2006) and DiNardo et al. (1996) (DiNardo, Fortin and Lemieux – DFL henceforth). The method was developed to create counterfactual wage distributions by holding the skill composition of the work force constant and letting all other dimensions of wage determination change.[31] First, between any two given years, t and $t-k$, I run a probit regression on the pooled sample of the two years, by including education and experience variables on the right hand side and with an indicator variable of being present in the sample of year t on the left hand side. After having the predicted values, $\hat{p}$, for the conditional probability of being sampled in t, the new sample weights for year $t-k$ are calculated as

$$\Psi_{t-k} = \frac{\hat{p}}{1-\hat{p}} \psi_{t-k},$$

where Ψ_{t-k} represents the new set of weights and ψ_{t-k} the old one; and $\Psi_t = \psi_t$.[32] After having constructed the counterfactual skill distributions, one can compute inequality indices based on the new and old set of weights, and any difference between the two set of measures demonstrate to which extent changes in skill composition influence changes in the dispersion of earnings.

[31] In the Eastern European context, Ganguli and Terrell (2006) applied the method of DiNardo et al. (1996) to construct counterfactual kernel densities of wages for Ukraine and to do a Lemieux (2002) and Juhn et al. (1993) type of decomposition analysis.

[32] For more details, please refer to DiNardo et al. (1996).

Tables 1.4a and 1.4b demonstrate the results of this exercise for interdecile differentials of log monthly earnings for four sub-periods. The second column lists the resulting counterfactual changes in the inequality measures when holding the composition of work force constant, but letting the minimum wage increase between 2000 and 2002. The third column only differs from the second for this period, since I control both for the minimum wage increase and for composition effects.

The last two columns report the corresponding shares of actual changes in inequality explained by composition effect. For 2000-2002, inequality changes without composition and minimum wage effects are compared to inequality changes without the minimum wage effect reported in column two of Table 1.3. That is, in the last column I answer the question: To what extent would have composition changes contributed to total inequality change, had the minimum wage been fixed at its 2000 level? The interpretation of signs behind numbers is the same as in Table 1.3: if inequality changes due to changes in worker composition point to the same direction as the actually measured change in inequality, I report a plus sign, while a minus sign if the opposite is true. For example, although the actual 90-10 differential declined in 2005-2008 for women, changes in skill composition increased inequality, and the fall in the measure would have been 27 percent bigger, had the composition remained as it was in 2005.

In every case, for both genders, changes in skill composition geared up wage dispersion.[33] For women, setting aside the 2000-2002 period for a moment, the magnitude of the effect is around 30 percent for the 90-10 differential, 30-40 percent for the 90-50 differential, and around 20 percent in case of the 50-10 measure. For men, we see similar numbers, except for the 90-10 and 50-10 differentials in the very last sub-period when the effect of composition seems to disappear.

Concerning years 2000, 2001 and 2002, the positive composition effects above the median might look huge, but note that the base for the calculation of the contribution in percentages is very small, only three percent. Note also that the small composition effects for the 50-10 differential do not provide evidence of large employment effects of the minimum wage change, at least not of a

[33] The only exception is the male 50-10 differential in 2005-2008, but the composition effect is negligible.

nature that would alter the observable skill composition of the work force. If a lot of low-skilled workers had lost their job as the real minimum wage was rising, we would expect to see much higher inequality increasing composition effects below the median. Nonetheless, the *sign* of the composition effect is consistent with such a hypothesis. Finally, the table shows that the minimum wage increase not only affects the level of inequality, but also makes the role of composition changes seem smaller.

1.4.4.3. JMP decomposition

Up to this point, I dealt with observable factors of wage inequality changes. In this subsection I use the decomposition method of Juhn et al. (1993) based on residual imputation (Juhn, Murphy and Pierce (1993) – JMP henceforth). The motivation is that when constructing counterfactual wage distributions, one is not only interested in how changes in observable factors contributed to changes in wage dispersion, but also, how changes in unobservables, especially changes in returns to unobserved skills affected the distribution.

To address this problem, Juhn et al. (1993) suggest a two-step procedure. Take two years, t and $t-k$ and run Mincer wage regressions for each year separately. In the first step, choose a residual from the regression in t, find its rank in the distribution and replace it by the residual from the regression in $t-k$ with the same rank. Then, in the second step, replace the returns to observables, that is, the estimated coefficients from the Mincer regressions.

In other words, the method moves from the actual distribution in $t-k$ to the actual distribution of t, by holding the distribution of residuals (at least under the strict assumption of rank preservation) and the returns to observables fixed step-by-step, which breaks actual differences of the distributions into three parts: one due to differences in unobserved characteristics and returns to these characteristics (represented as one term by the differences in residuals); one due to differences in observable characteristics; and one due to differences in returns to observed characteristics. The JMP method builds on some fairly strong assumptions, but it is a computationally simple way of assessing the importance of unobserved factors in the evolution of wage inequality.[34]

Results of the decomposition of interdecile differentials are presented in Tables 5a and 5b. The underlying Mincer wage regressions include log real wages as the dependent variable and education, experience, and industry and region effects as control variables. Contributions of the three factors are displayed in percentages of the total change in inequality in the respective period. A negative value indicates a counter effective contribution, that is, one that is of opposite sign than the total change in inequality.

Note that contributions of observable quantities are not to be compared directly to composition effects estimated by the DFL reweighting method, not only because the two methods are very different, but also because while in the previous subsection I was interested in the effects of skill composition, here the main focus is the share of unobserved factors and thus, I also allow for changes in the distribution of the work force across industries and regions to explain as much variation in wages as possible by observed variables.

The share explained by unobservable composition and prices is quite high, roughly speaking about half the total change in inequality. In some cases, it is even higher, for example, the rise in male inequality below the median between 2002 and 2005, and the drop in male inequality above the median between 2005 and 2008 is explained 77 and 72 percent by unobservables, respectively. In general, the role of unobserved characteristics and returns is more dominant for changes in the male distribution than for women.

The shares for 2000-2002 and for the 90-50 differential are huge, but again, the underlying overall change in the measure is very small. In contrast to the previous subsection, now we get a substantial effect for observed worker composition below the median during the period of the minimum wage increase, moreover, the effect is negative. When holding also the minimum wage fixed – similarly to the exercise in the columns marked by (2) in Tables 4a and 4b – then almost 90

[34] For the detailed description of the JMP residual imputation method see Juhn et al. (1993), while on limitations and advantages of the method relative to other alternatives see Fortin et al. (2011).

percent of the drop in the 90-50 differential is explained by quantity effects.[35] Whether this is the consequence of employment effects of the minimum wage that we cannot filter out with the DFL method because one of its main assumptions is violated, or the effect of some other factors remains a question of further research.

1.5. Conclusions

Wage inequality analysis has been one of the most prolific areas of labor market research in the last two decades, and this paper contributes to the literature by examining trends in the dispersion of wages in a transition economy over a long period of time, spanning the last years of socialist regime and eighteen years after the transition to market economy. Hungary experienced numerous changes during this time that strongly affected the determination of wages in the labor market, so we might expect that the shape of the earnings distribution changed dramatically within a very short period.

Indeed, the distribution of wages in the Hungarian corporate sector was tightly compressed during socialist rule but spread out rapidly after transition. Also, changes in minimum wage legislation introduced a new mode in the bottom part of the density. The unconditional male and female distributions converged, but within each group, by 2000, wage inequality exceeded by close to seventy percent its level in 1986, as measured by the log 90-10 differential. For low-wage quantiles, this process was coupled with a continuous decline in real earnings that created a possible source for social discontent. 2000 also marked the peak year in earnings inequality when the 90-10 interdecile differential was the highest among OECD countries.

Between 2000 and 2002, the government increased minimum wages in two steps that diminished the distance of the lowest decile of the wage distribution from the median, but inequality in the upper half of the distribution kept on rising. Moreover, if one constructs a counterfactual distribution of 2002 wages that would prevail had the minimum wage remained at its 2000 level, counterfactual changes between the two periods suggest that although the rise in the

[35] Corresponding results are not presented here but available from the author upon request.

minimum wage is a major explanation behind the decline in inequality, but inequality would have decreased somewhat even in the absence of government intervention.

After 2002, wage dispersion in general was on the rise until 2005, but the trend turned and the years between 2005 and 2008 are marked by diminishing inequality. However, the top quartile of the distribution does not exhibit the ups and downs in overall inequality: dispersion of wages among the highest earners was basically growing throughout the observed period.

Besides the usual indicators of wage inequality, like the standard deviation, log differentials and the Gini coefficient, I investigated changes in the wage distribution using a number of alternative measures of dispersion with some desirable properties that were developed in the income inequality literature. These measures belong to the General Entropy Class of inequality indices, and possess a parameter that calibrates the measure's sensitivity to changes in particular parts of the distribution. Although the general tendencies depicted by these alternative indices are similar, in a number of years, there are differences not only in the magnitude but in some cases also in the direction of measured inequality changes. This shows, first that policy makers have to proceed with care when considering only single indicators of dispersion, and second, that measures with sensitivity parameters might be useful in pointing out where changes in the distribution of wages primarily took place.

Having established the main patterns of inequality changes, I considered several factors that might have triggered these tendencies. First, it is possible that an increasing inequality of earnings is only an artifact of increased dispersion in the number of hours worked. Unfortunately, the dataset used for the analysis only contains monthly earnings for all the years, but for 2002-2008 it was possible to construct two measures of hourly earnings: One for which I divided monthly earnings by weekly regular hours, and another for which the denominator was the number of actually paid hours over the month. Of course, the second is more appropriate to account for the possibility that a part of the growth in inequality is simply due to higher working hours worked by a fraction of employees. In reality, this does not seem to be the case – as far as the hourly measures are good proxies for the true hourly wage – since the patterns in inequality of hourly earnings are very similar to monthly figures. Hours actually paid do account for a little part of the growth in inequality, suggesting that high wage workers also work more, but it is evidently not the leading explanation.

On the other hand, changes in the skill composition contributed to a great extent to changes in wage dispersion, especially in the first half of the nineties, and more so for men than for women. Huge changes in the composition by highest degree of education in particular contributed significantly to the steep rise in inequality between 1989 and 2000. These happened at all possible fronts: mean wages and within-group wage dispersion of different educational groups diverged, and the share of higher skilled groups – having higher mean wages and higher variance – increased.

Like skill composition in the nineties, the leading factor behind the abrupt drop in inequality between 2000 and 2002 was the rise in the minimum wage. About 60-70 percent of the decline in wage dispersion is due to the 57 percent increase in the real value of the minimum wage during these two years. Women are more heavily affected than men, and this policy change seem to also have influenced higher quantiles of the wage distribution indirectly. Nonetheless, decomposition results show that overall wage inequality would have also declined even in the absence of the government's decision, even if by far less.

Finally, a very interesting piece of evidence concerning future research is related to the role of employers. A major result in this paper shows that changes in overall wage inequality are reflected in between-firm inequality, but the within-firm component declines almost steadily during the sample period. When analyzing entering cohorts of firms, I found that the appearance of a large group of new firms in the first half of the nineties with high variance of wages was probably a main driving force of the pervasive inequality increase in the nineties. Interestingly, mean wages of different cohorts of firms evolve highly similarly, differing only because of differences in where these firms are in their life-cycle. If at all, then the differences in mean wages influenced overall inequality in that the employment share of the highest wage cohort – the group of firms born before transition – was decreasing constantly over time. A deeper investigation of the role of firm-level factors seems fruitful, and it might also decrease the still high unexplained share of changes in wage inequality.

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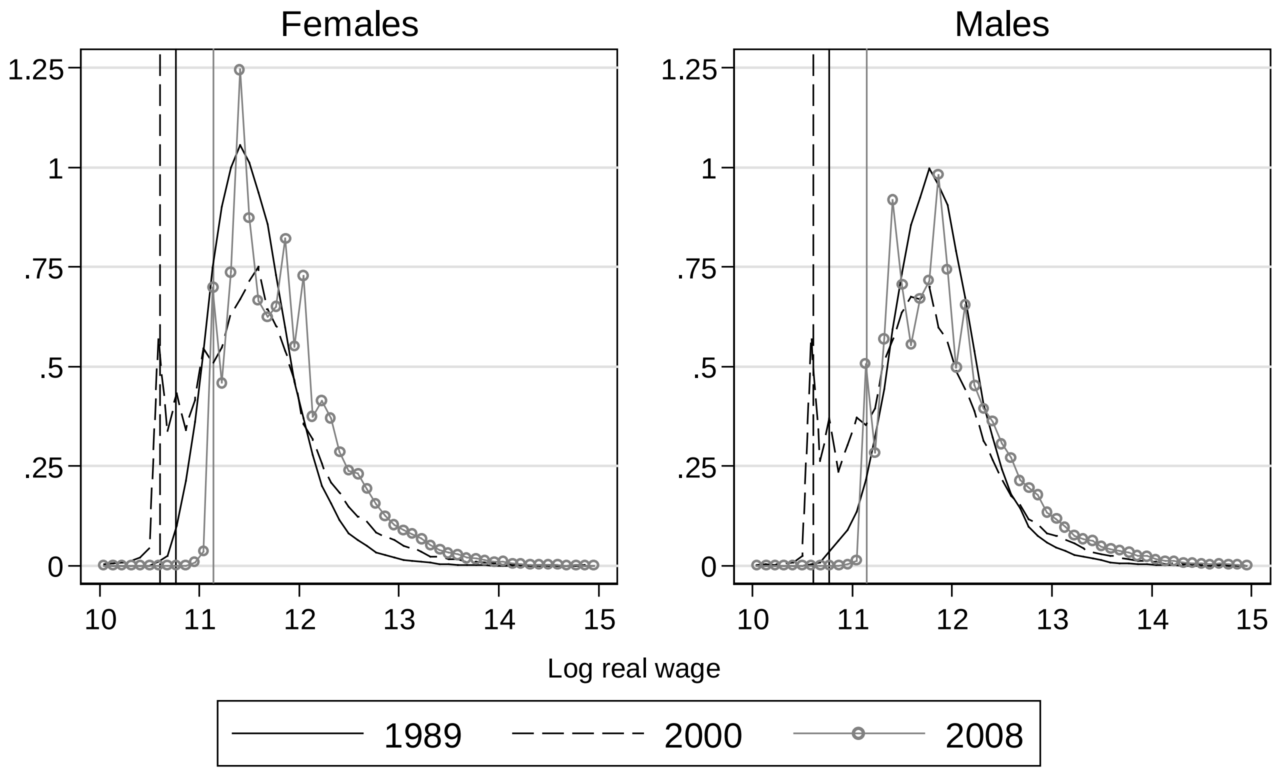
1.7. Tables and Figures

Figure 1.1: Kernel Density Estimates of Log Real Wages by Gender



Notes: N = 366,562 in 1989; 121,051 in 2000; and 125,667 in 2008. Vertical lines mark the real value of the minimum wage in a given year. Log real wages expressed as logarithm of gross monthly earnings in 2008 Hungarian forints. Earnings refer to all payments defined as earnings by the Hungarian Statistical Office, received by the employee in the month of the survey at the expense of the employer's wage cost account, plus one-twelfth of all non-regular premia, bonuses, commissions and of thirteenth-month salary earned in the previous year (tenure-adjusted if employee was hired in previous year). Results are weighted.

Figure 1.2a: Evolution of the Minimum Wage and Mean Wages (1989=100)

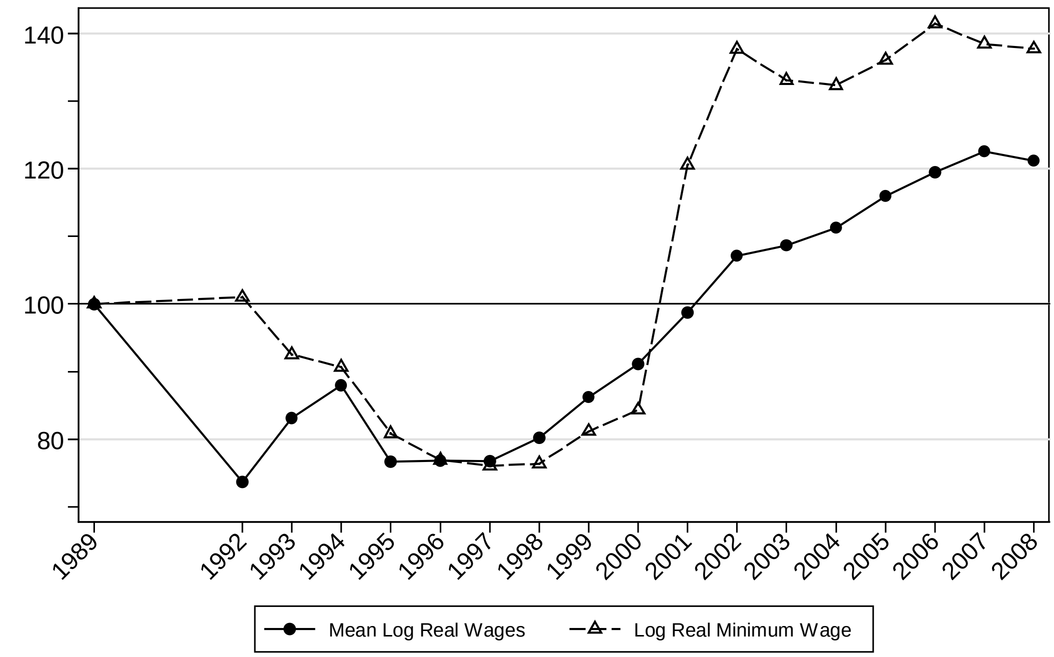
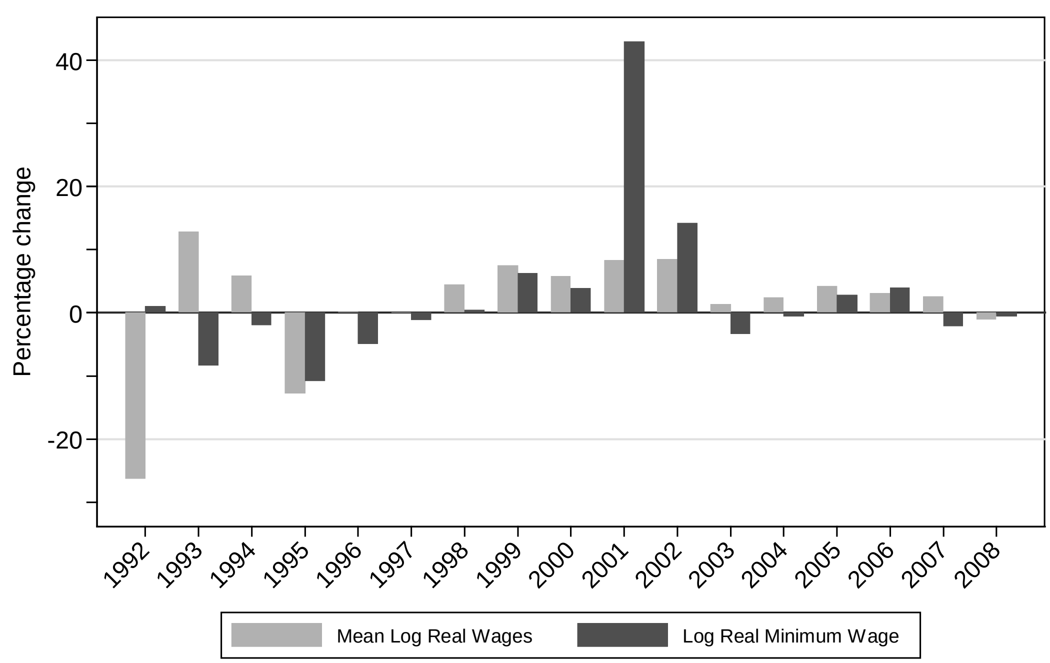
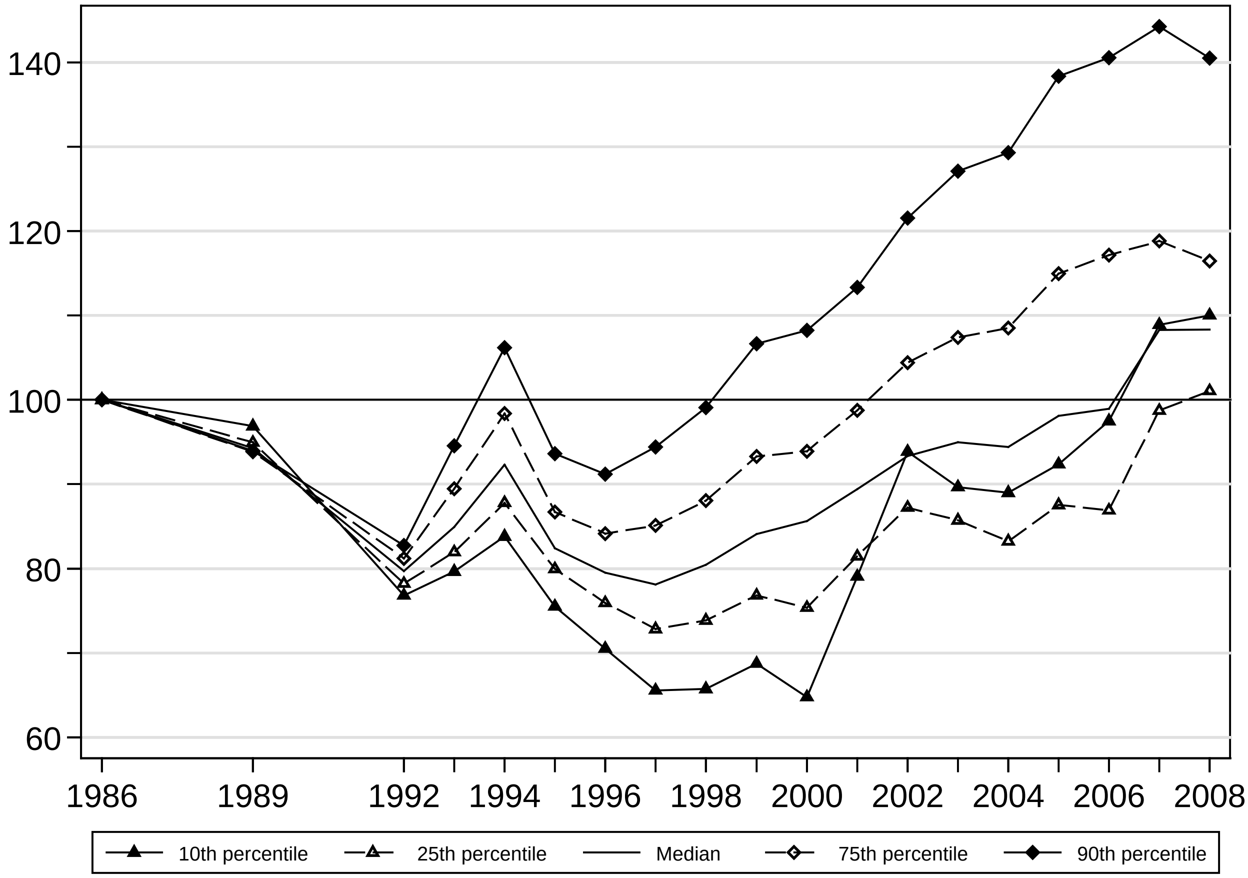


Figure 1.2b: Year-on-Year Changes in the Minimum Wage and in Mean Wages



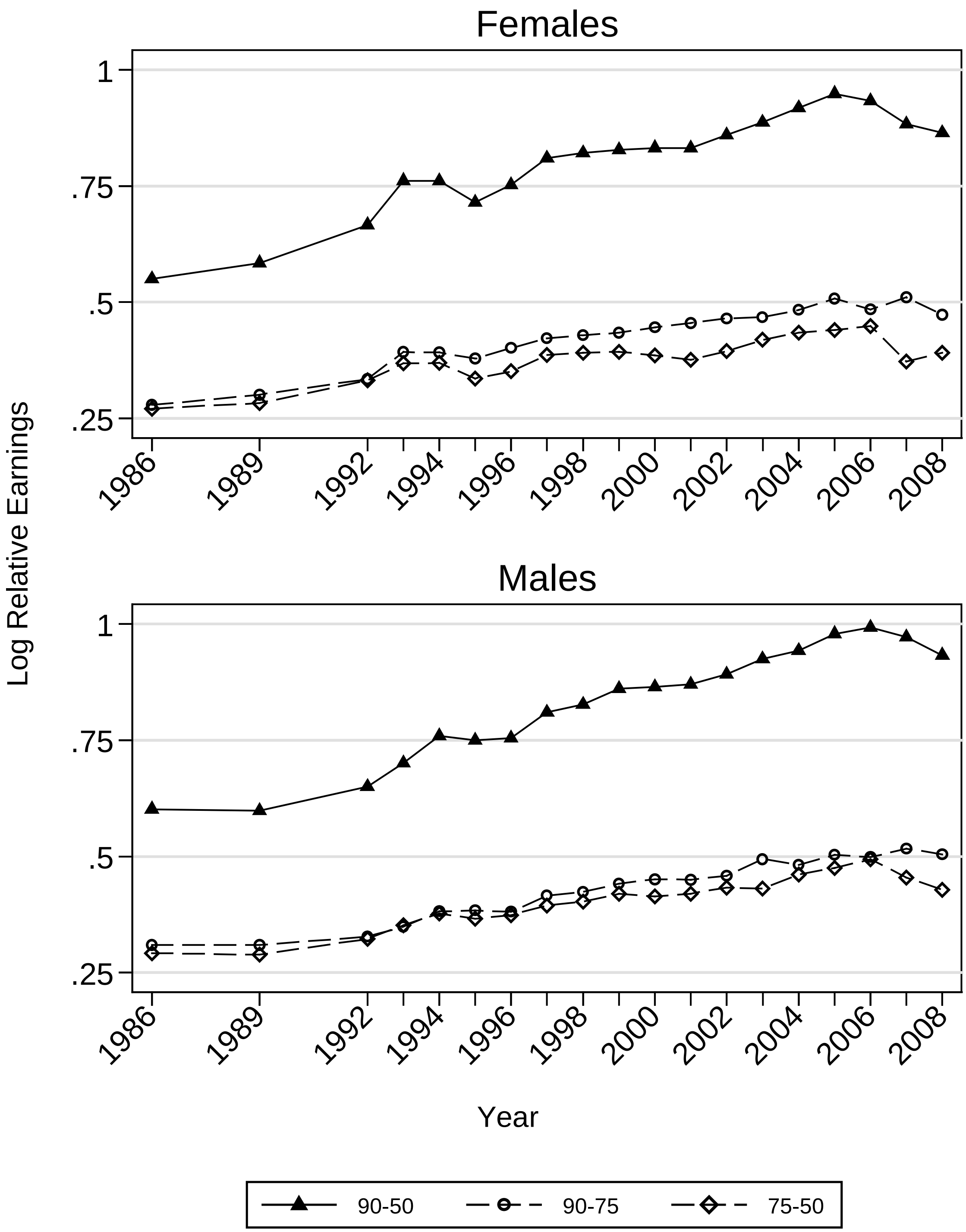
Notes: Changes in mean wages computed from a pooled regression of log wages on year dummies and firm fixed effects to control for changes in firm composition over time. The evolution of mean wages follows closely aggregate data published by the Central Statistical Office. For the definition of wages, see the notes to Figure 1.1.

Figure 1.3: Real Monthly Wages by Percentile
(1986=100)



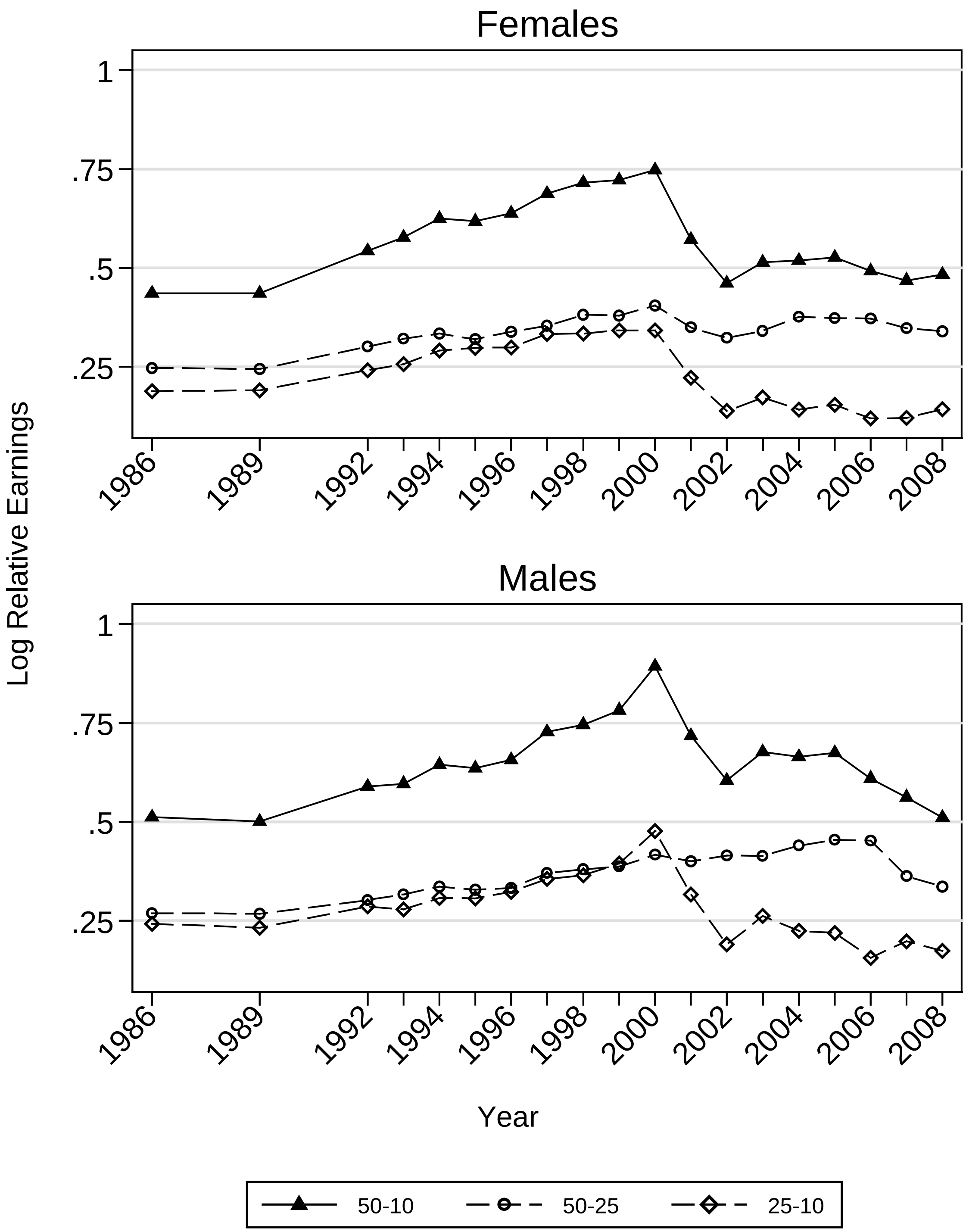
Notes: Each series normalized by its own starting value in 1986. For the definition of wages, see the notes to Figure 1.1.

Figure 1.4a: Interquantile Wage Differentials in the Top Half of the Wage Distribution



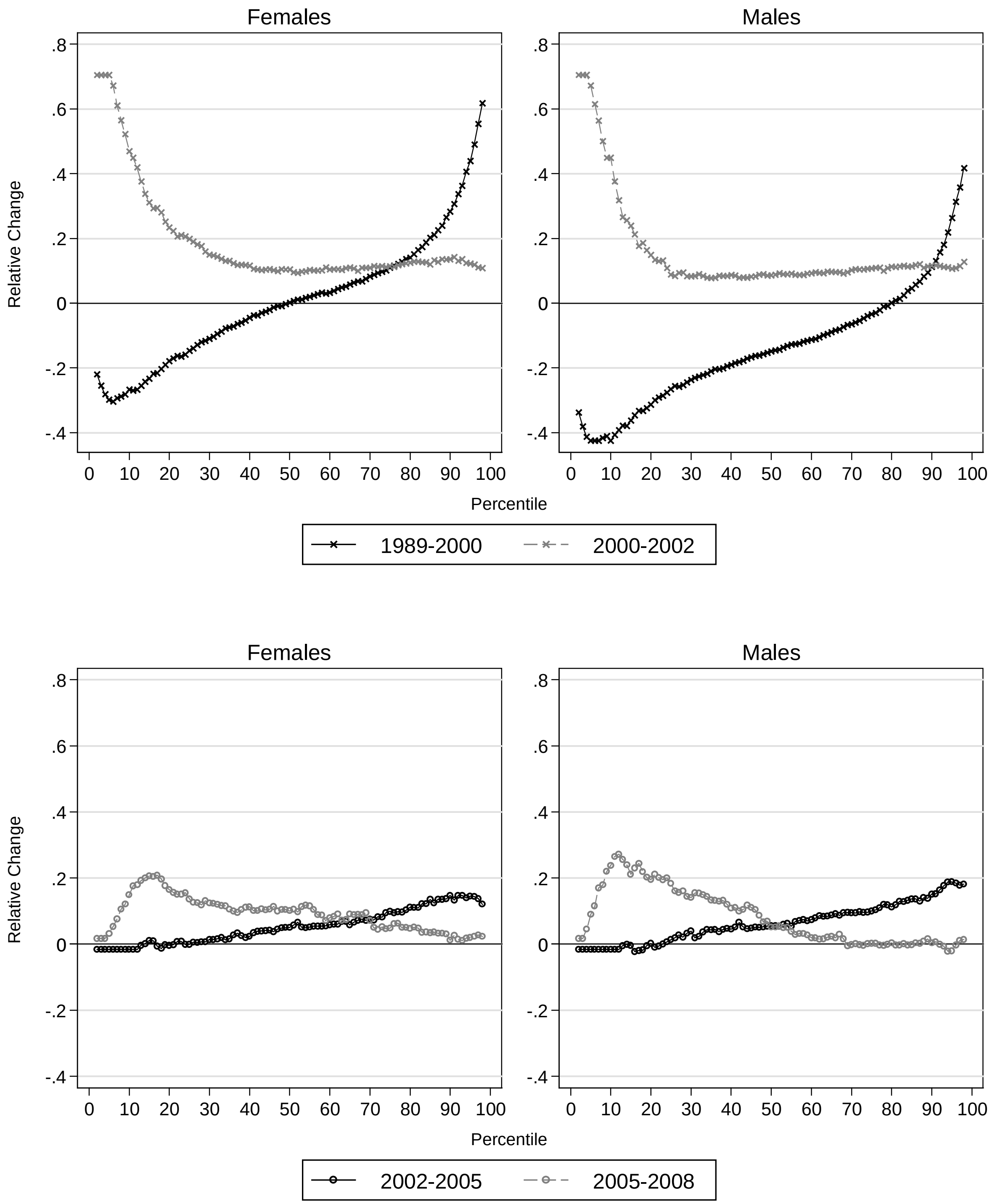
Notes: Differences between respective quantiles of the log wage distribution. For the definition of wages, see the notes to Figure 1.1.

Figure 1.4b: Interquantile Wage Differentials in the Bottom Half of the Wage Distribution



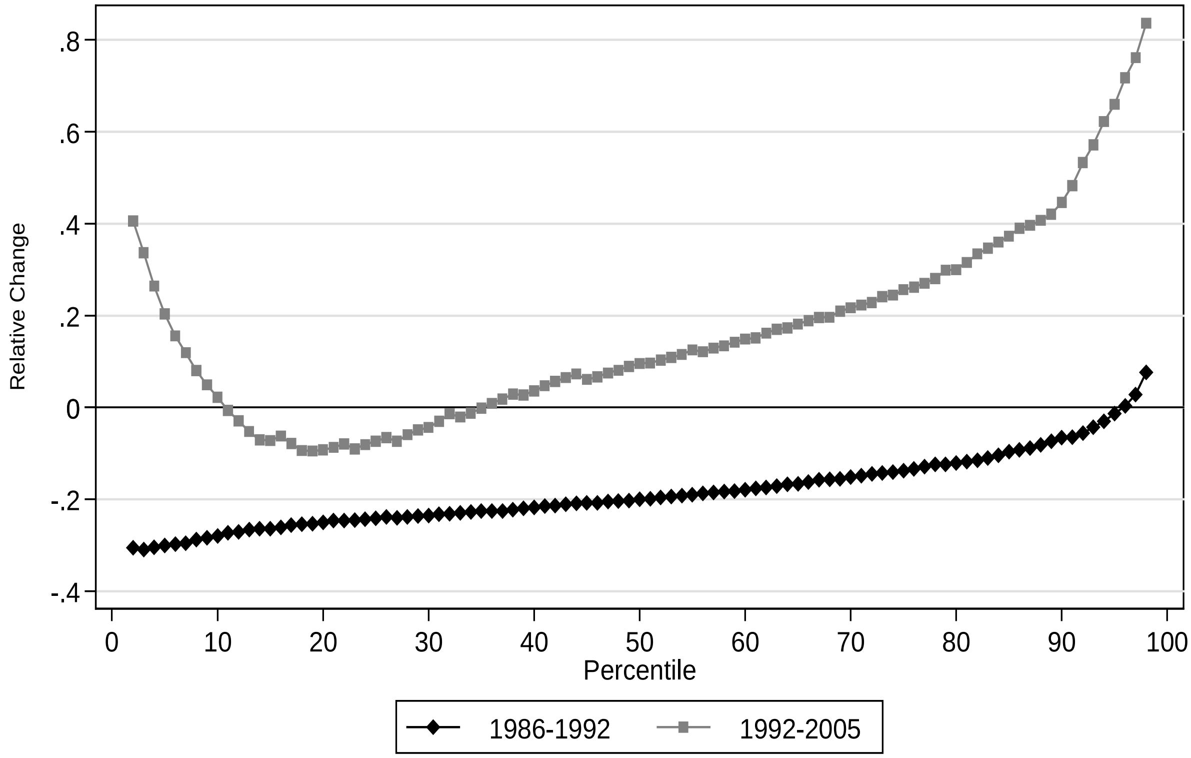
Notes: Differences between respective quantiles of the log wage distribution. For the definition of wages, see the notes to Figure 1.1.

Figure 1.5: Changes in Real Earnings by Percentile



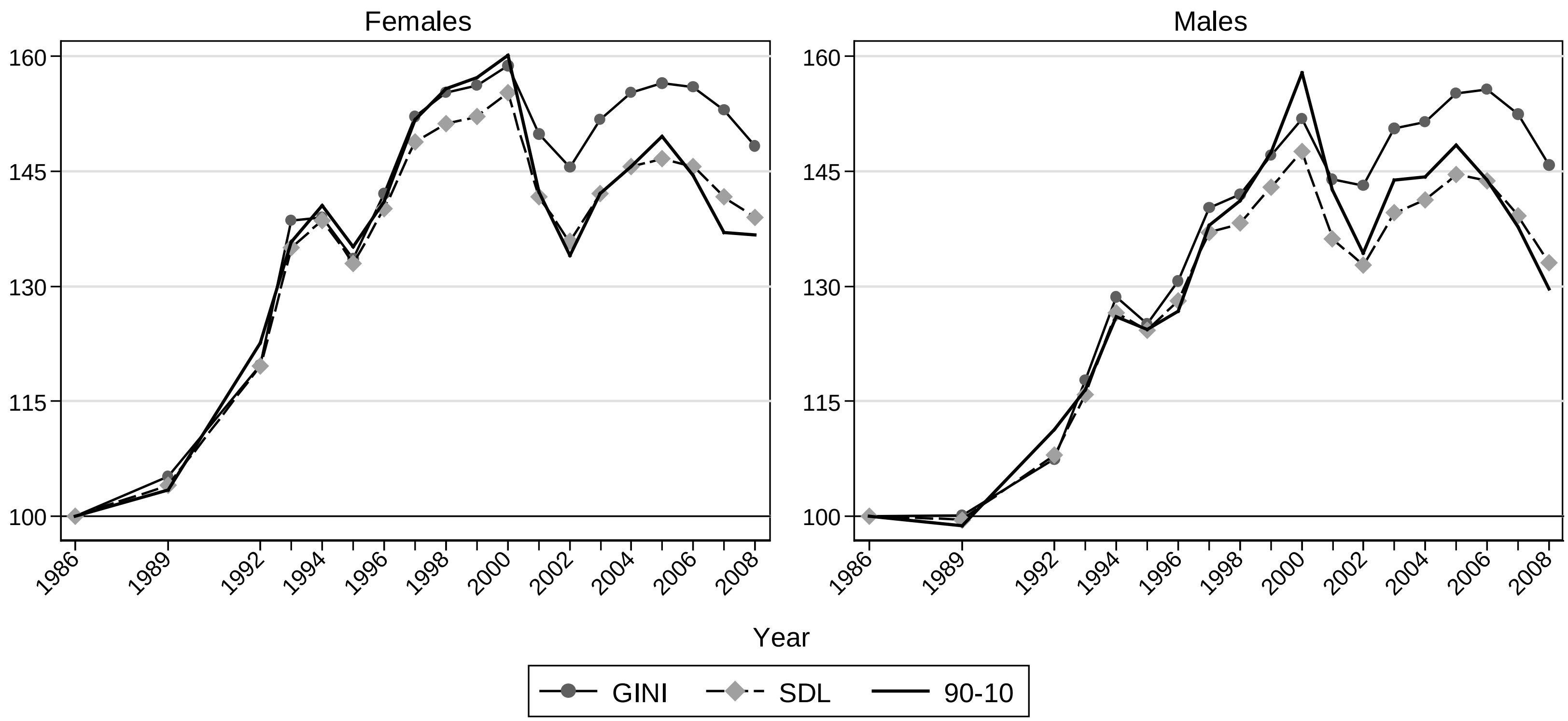
Notes: The graphs plot relative changes in the level of real wages for the 2nd-98th percentiles of the wage distribution between respective years. The first and 99th percentiles were dropped due to outlier problems. For the definition of wages, see the notes to Figure 1.1.

Figure 1.6: Changes in Real Earnings by Percentile, Men



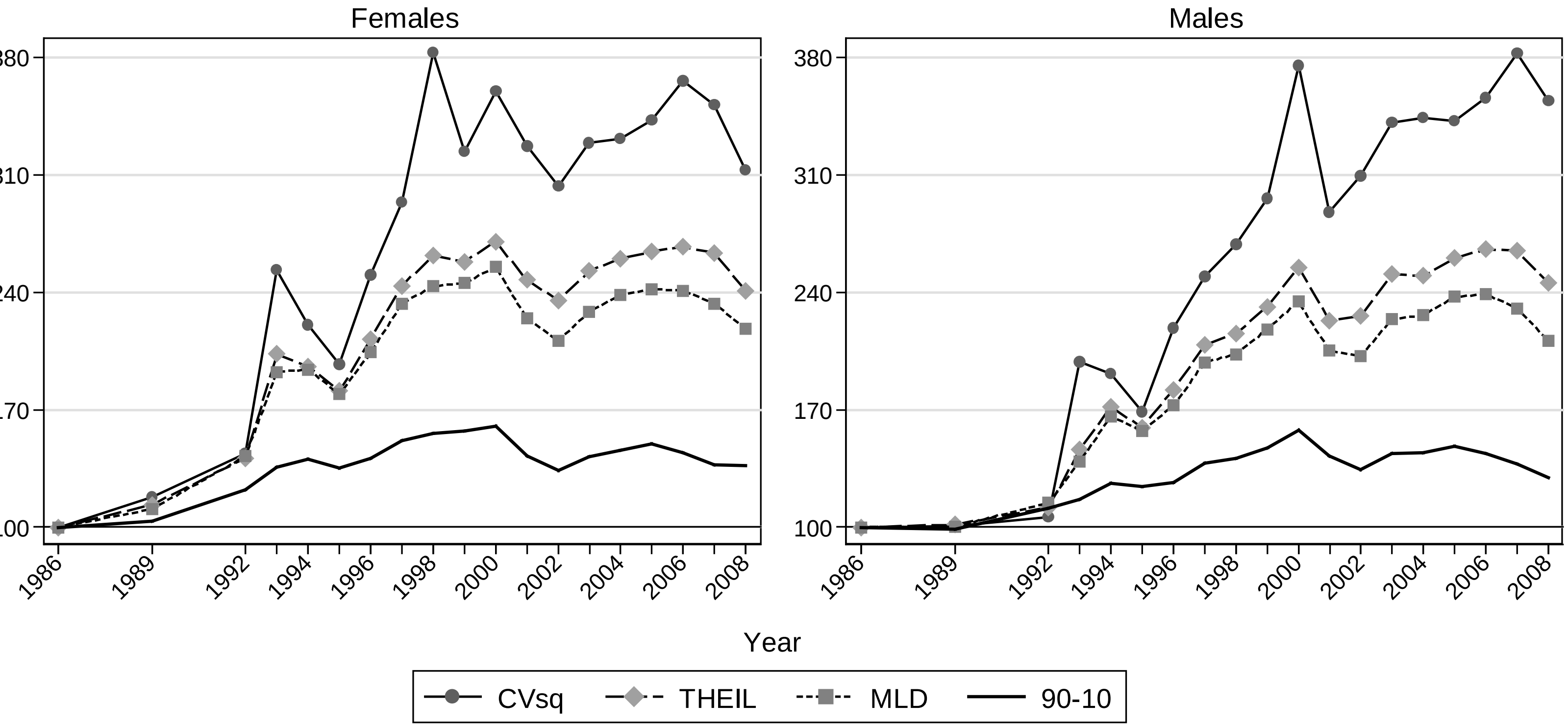
Notes: See the notes to Figure 5.

Figure 1.7a: Comparison of Inequality Measures I – Common Measures in the Wage Inequality Literature
(1986=100)



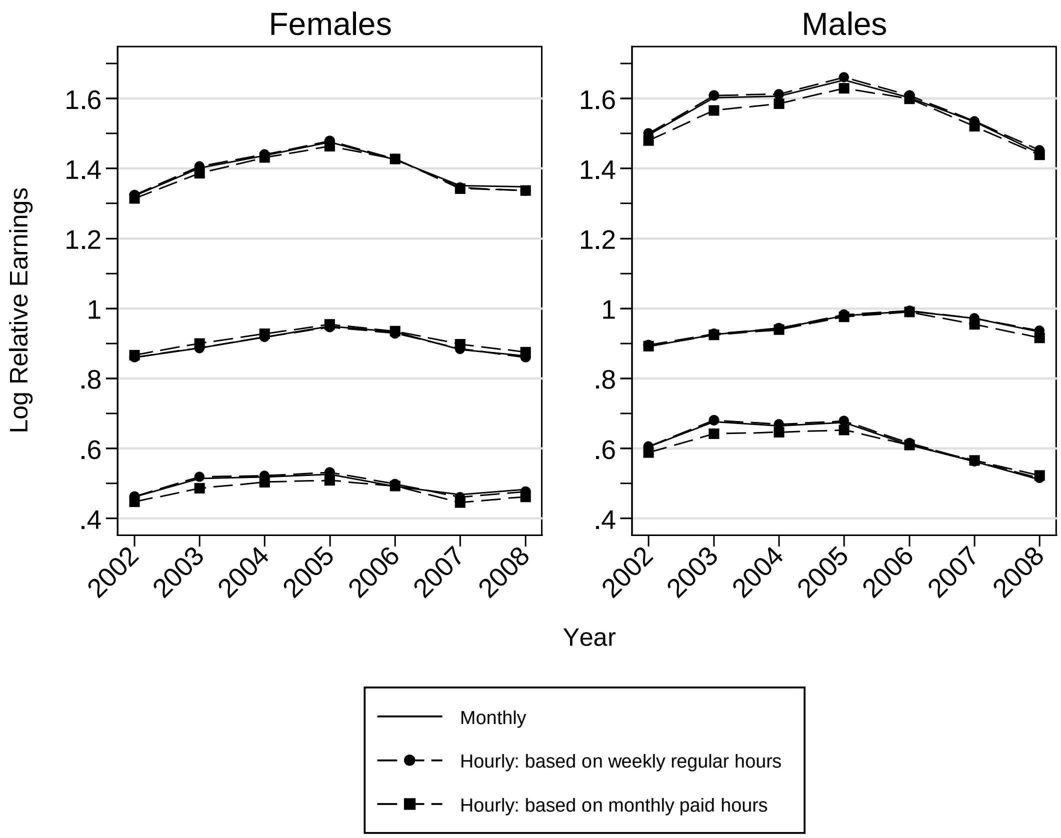
Notes: GINI = Gini coefficient; SDL = standard deviation of log wages; 90-10 = log 90-10 interdecile differential.

Figure 1.7b: Comparison of Inequality Measures II – The General Entropy Class
(1986=100)



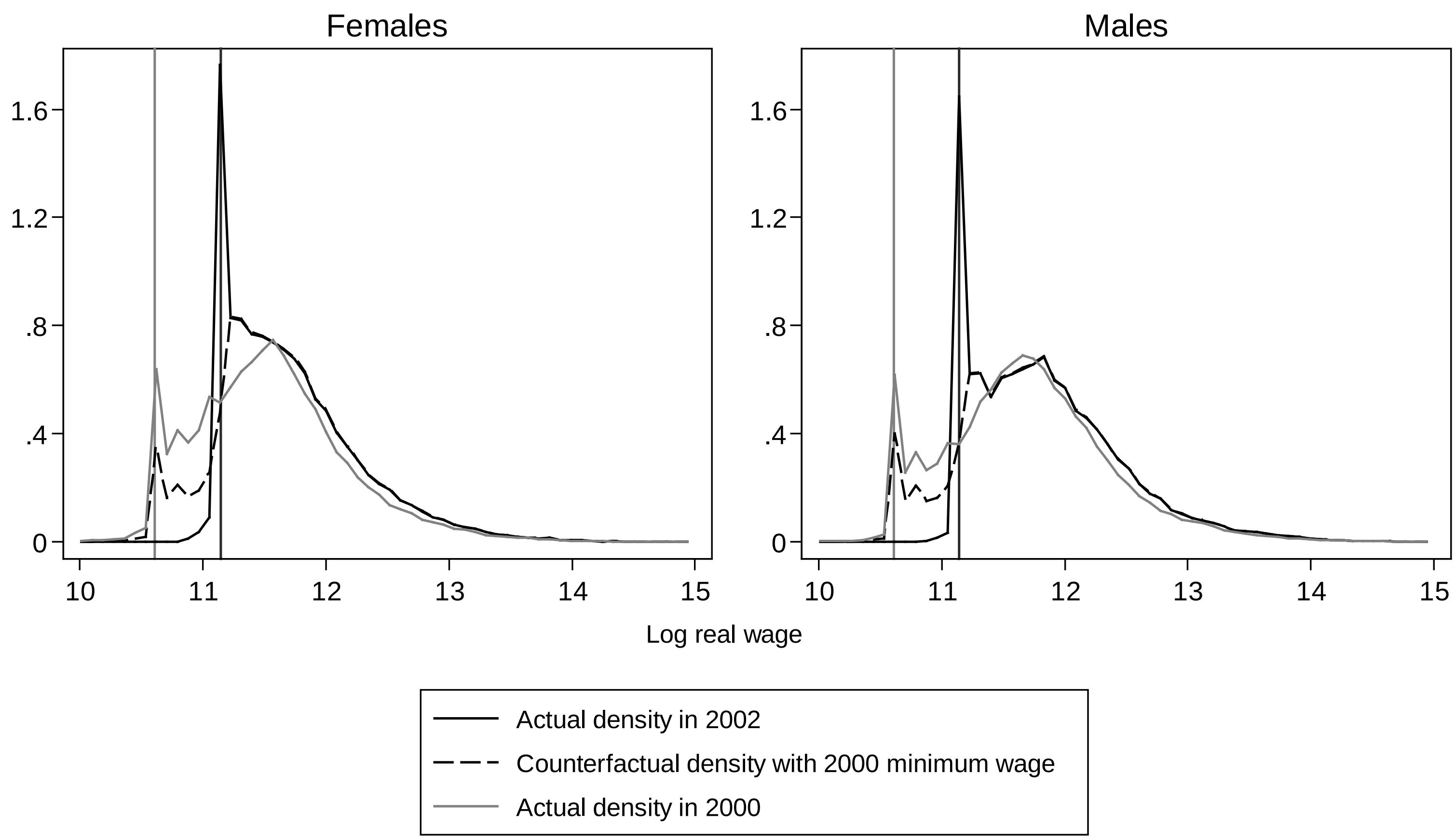
Notes: CVsq = two times the square of the coefficient of variation (corresponding to the general entropy measure with sensitivity parameter equal to two); THEIL = Theil index (corresponding to the general entropy measure with sensitivity parameter equal to one); MLD = mean logarithmic deviation (corresponding to the general entropy measure with sensitivity parameter equal to zero) ; 90-10 = log 90-10 interdecile differential. Please find the formal expressions of the measures in the text.

Figure 1.8: Dispersion of Monthly and Hourly Earnings, 2002-2008
Interdecile Differentials
(From top to bottom: 90-10, 90-50 and 50-10 differential)



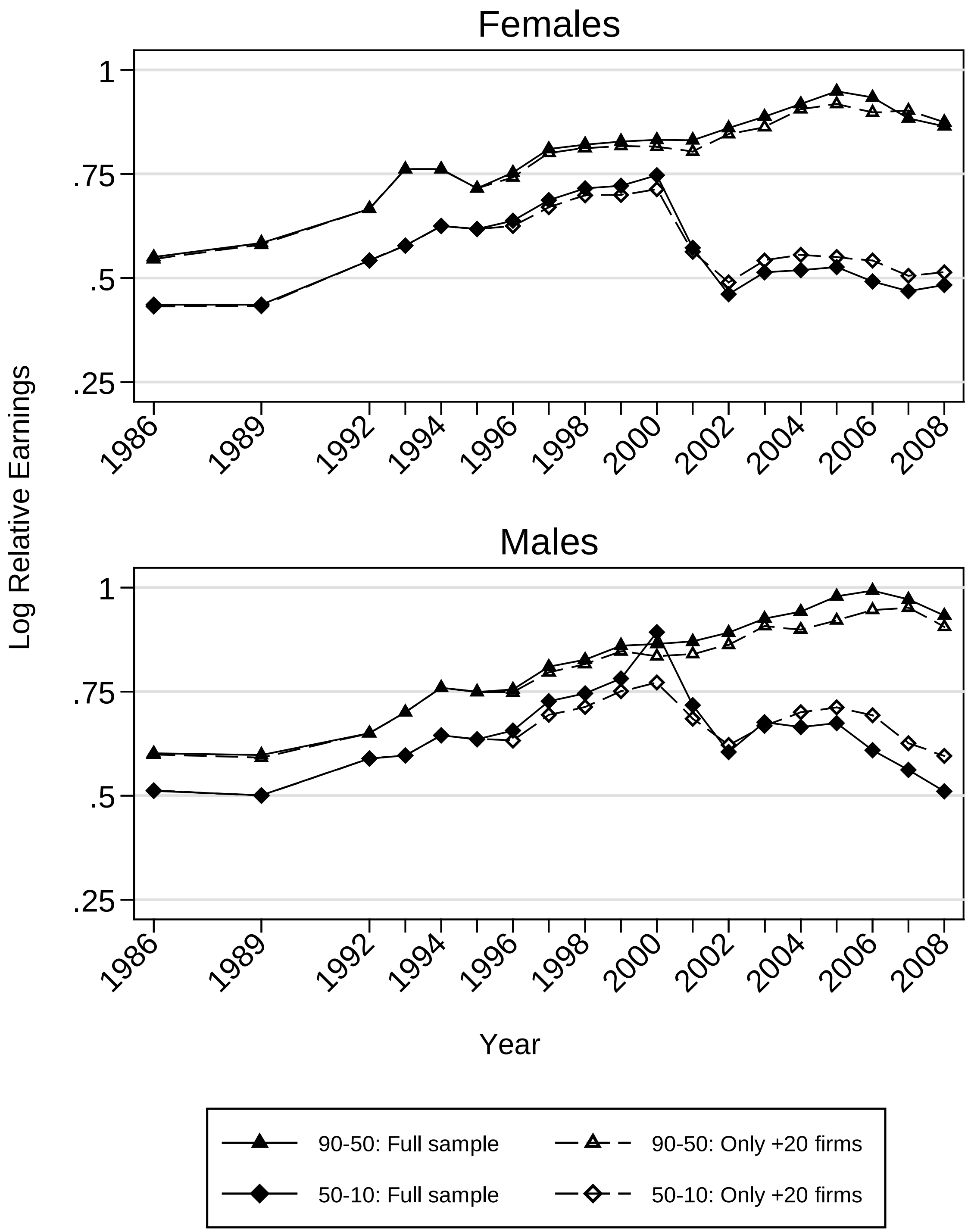
Notes: Hourly earnings are computed by subtracting from the log of monthly earnings either the log of actually paid hours over the month, or the log of four times weekly regular hours. Weekly regular hours determined by the employment contract of the employee. Both measures on working hours reported by the employer.

Figure 1.9: The 2002 Wage Distribution Adjusted for the Minimum Wage Increase



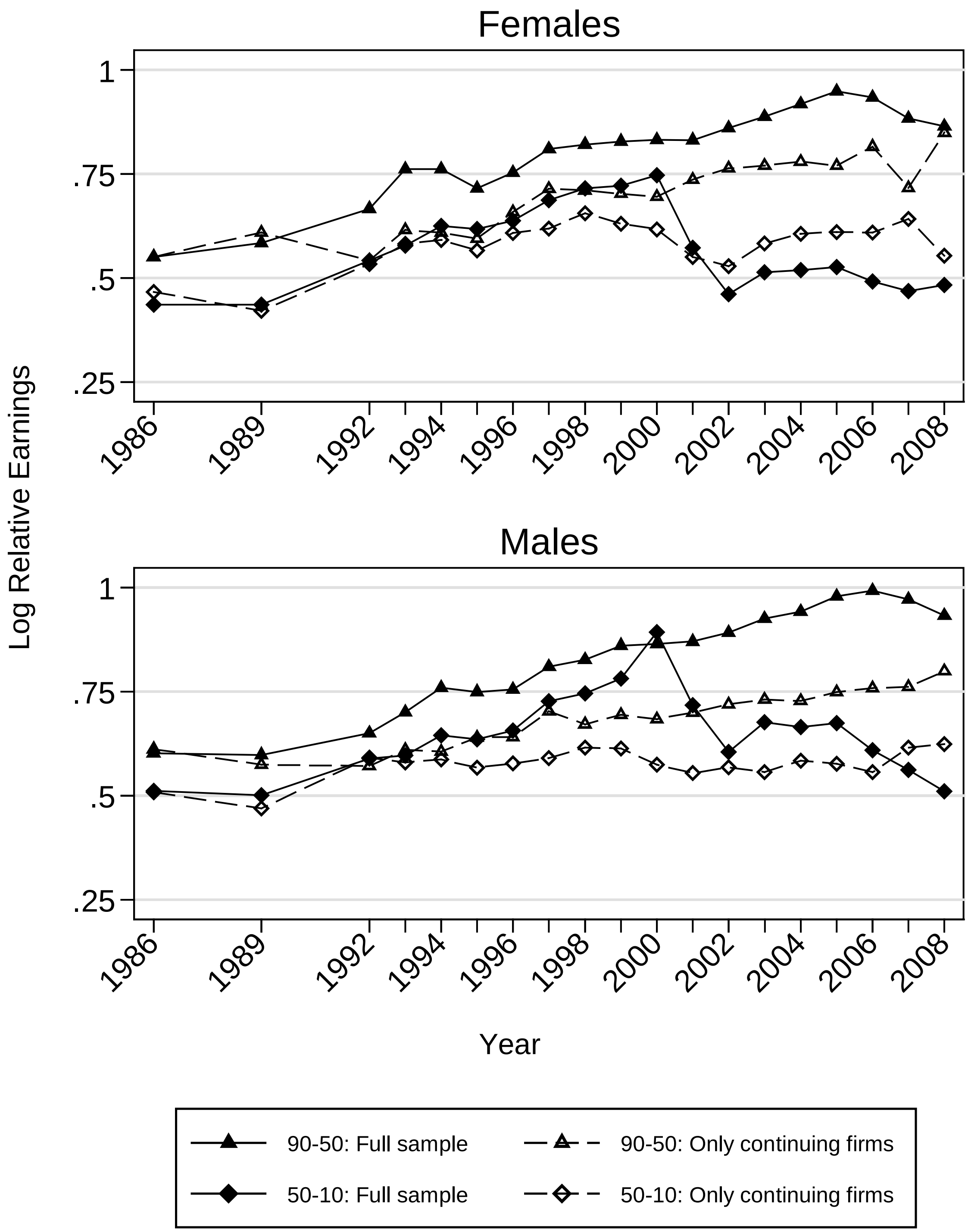
Notes: Counterfactual density: The density that would have prevailed in 2002, if the real value of the minimum wage had remained at its 2000 level. Real value of minimum wage in 2000 and 2002 marked by gray and black vertical lines, respectively. Actual density in 2002 reweighted below the minimum wage by the method of DiNardo et al. (1996). Above the 2002 minimum wage, the counterfactual density and the actual 2002 density of wages coincide by construction. For the definition of earnings, see Figure 1.1.

Figure 1.10: Interdecile Differentials in the Full Sample and in the Subsample of Enterprises with more than 20 Employees



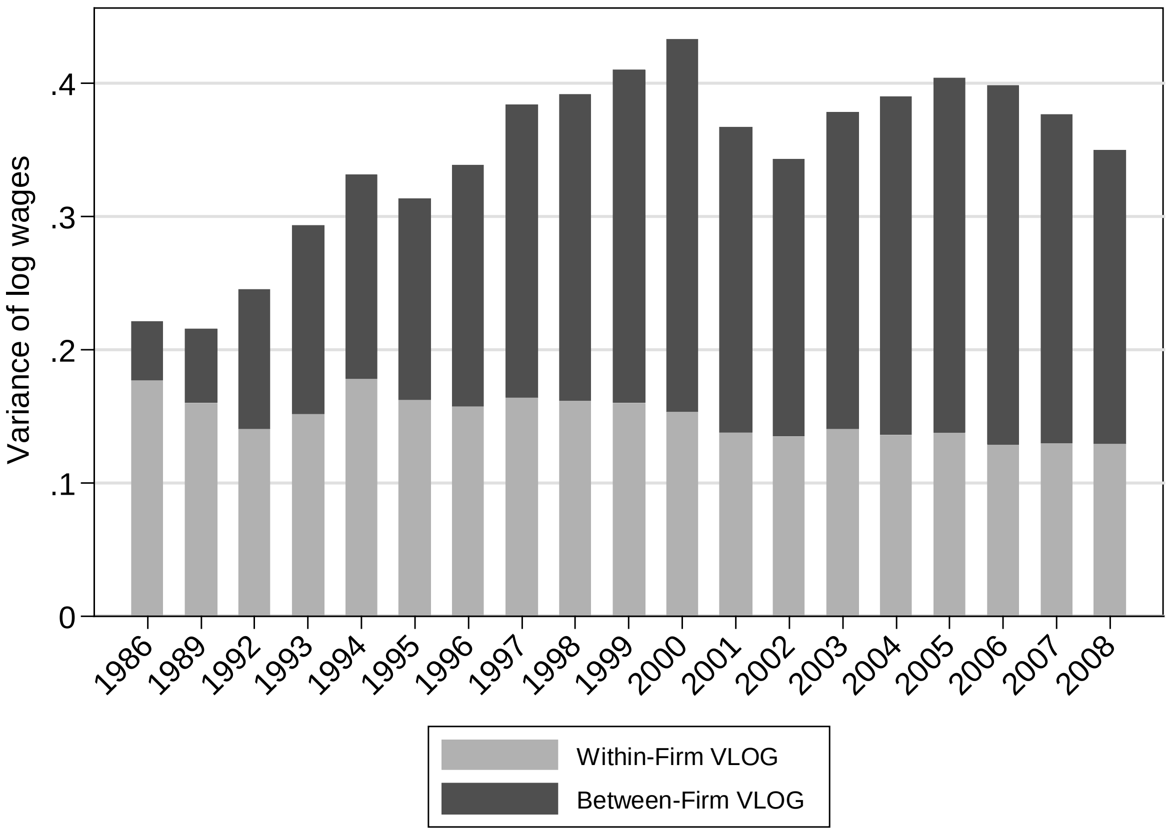
Notes: Until 1995, no firms with less than 21 employees are present in the full sample either. The HWS includes companies with 11-20 workers from 1996, and firms with 5-10 workers from 2000.

Figure 1.11: Interdecile Differentials in the Full Sample and in the Subsample of Continuously Operating Enterprises



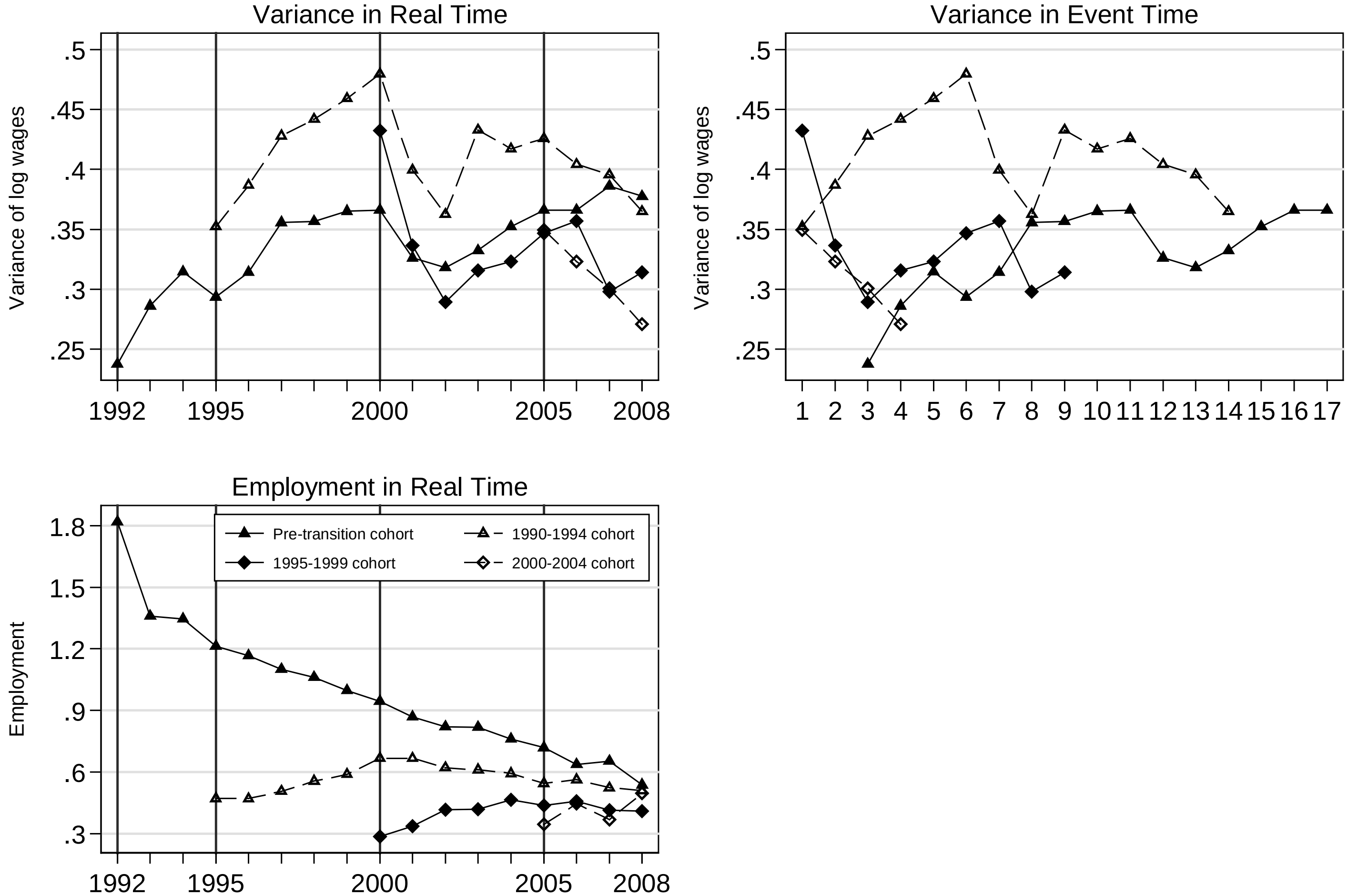
Notes: Continuously operating firms are the ones that are observed for at least 17 years out of 19 years spanned by the data.

Figure 1.12: Within-Firm and Between-Firm Variance of Log Wages



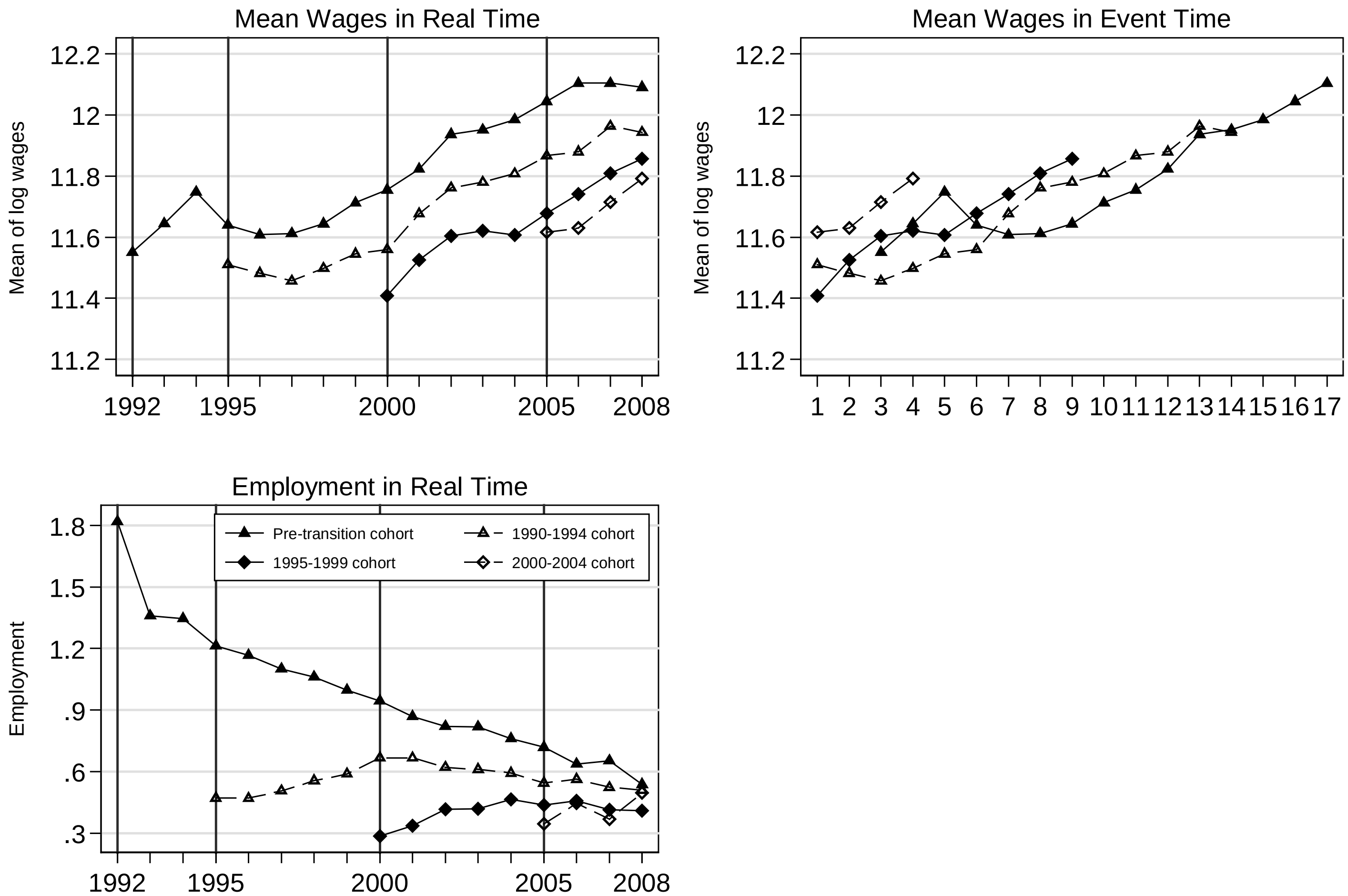
Notes: Results from a standard within-group/between-group variance decomposition performed by year, where groups of workers are defined as firms, and numbers of employees are used as group (firm) weights.

Figure 1.13a: Variance of Log Earnings by Cohorts of Firms



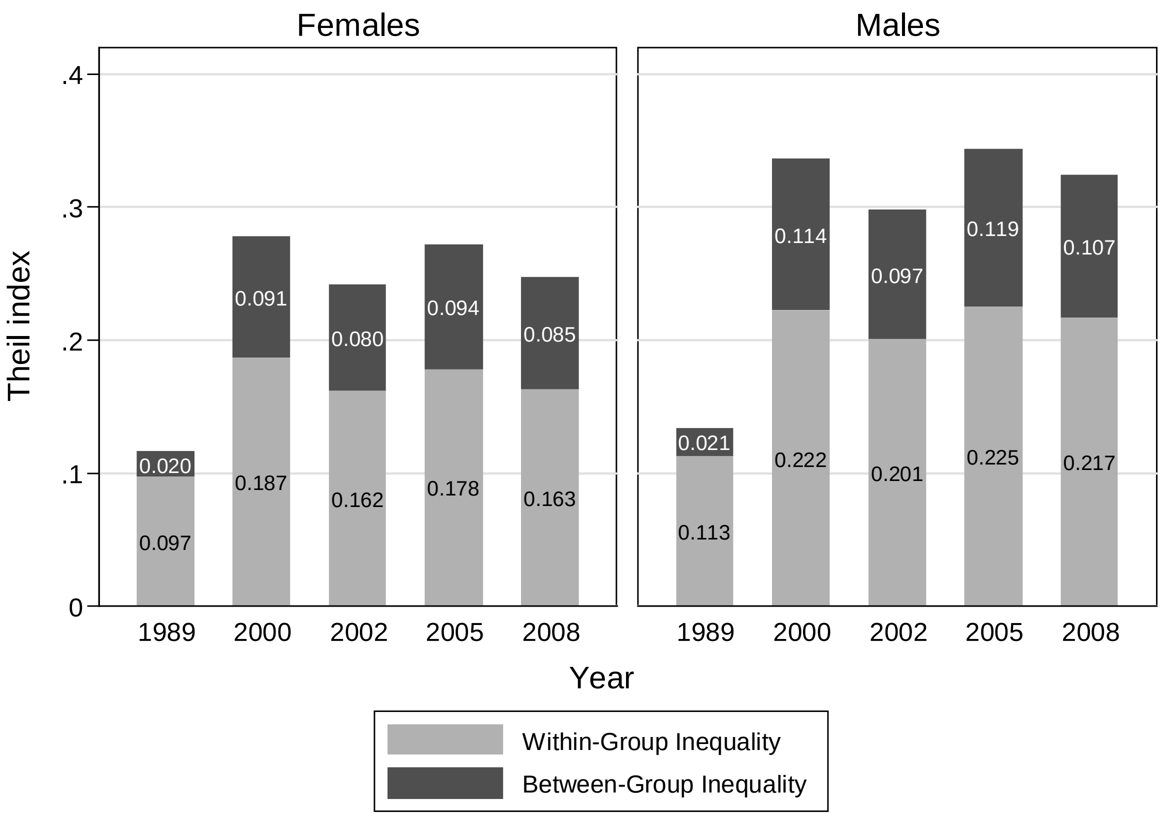
Notes: Information on entry from the comprehensive firm-level data of the Hungarian Tax Authority. Pre-transition cohort: firms observed before 1990, or having any positive state ownership share in at least one year. Other three cohorts: companies born in any of the indicated five years. For the event time analysis, the first years of observation for the respective cohorts (i.e. 1990, 1995, 2000 and 2005) are normalized to be year one. All results weighted by sample weights (i.e. also by size of firm). Employment in millions of workers.

Figure 1.13b: Mean of Log Earnings by Cohorts of Firms



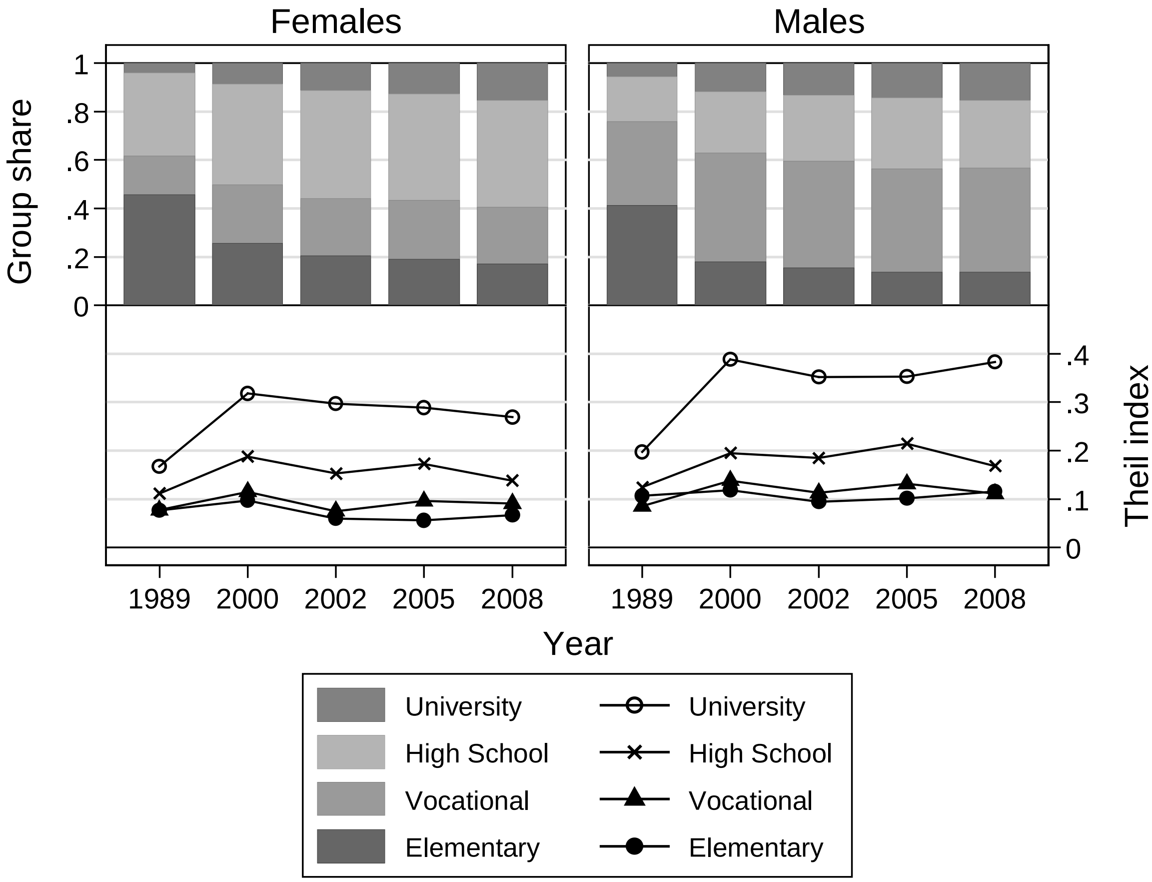
Notes: Information on entry from the comprehensive firm-level data of the Hungarian Tax Authority. Pre-transition cohort: firms observed before 1990, or having any positive state ownership share in at least one year. Other three cohorts: companies born in any of the indicated five years. For the event time analysis, the first years of observation for the respective cohorts (i.e. 1990, 1995, 2000 and 2005) are normalized to be year one. All results weighted by sample weights (i.e. also by size of firm). Employment in millions of workers.

Figure 1.14a: Decomposition of the Theil Index by Education Groups



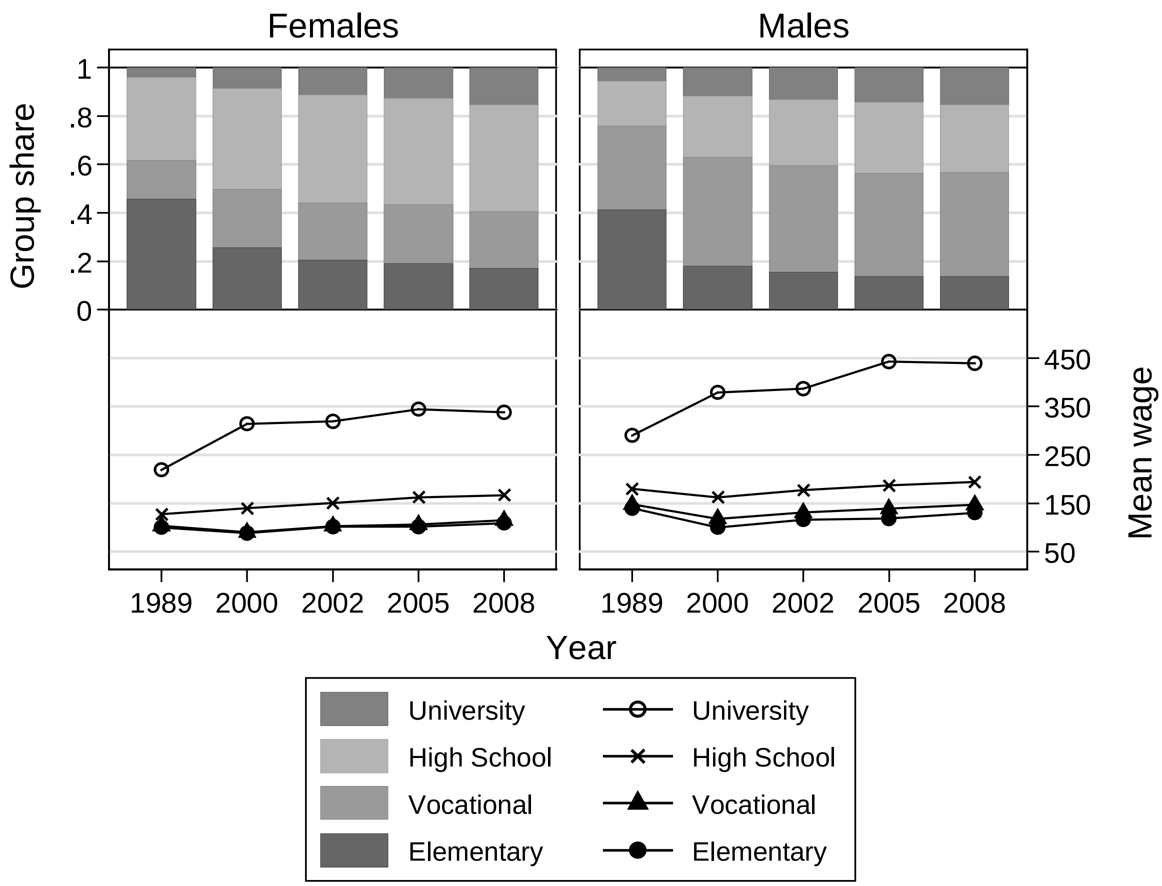
Notes: Results of Shorrocks (1980) decomposition of the Theil index by four subgroups according to highest level of education. The groups are: finished elementary education or less, finished vocational education, high school degree, college/university degree. Height of bars shown by bar labels.

Figure 1.14b: Within-Group Inequality and Population Shares by Education Groups



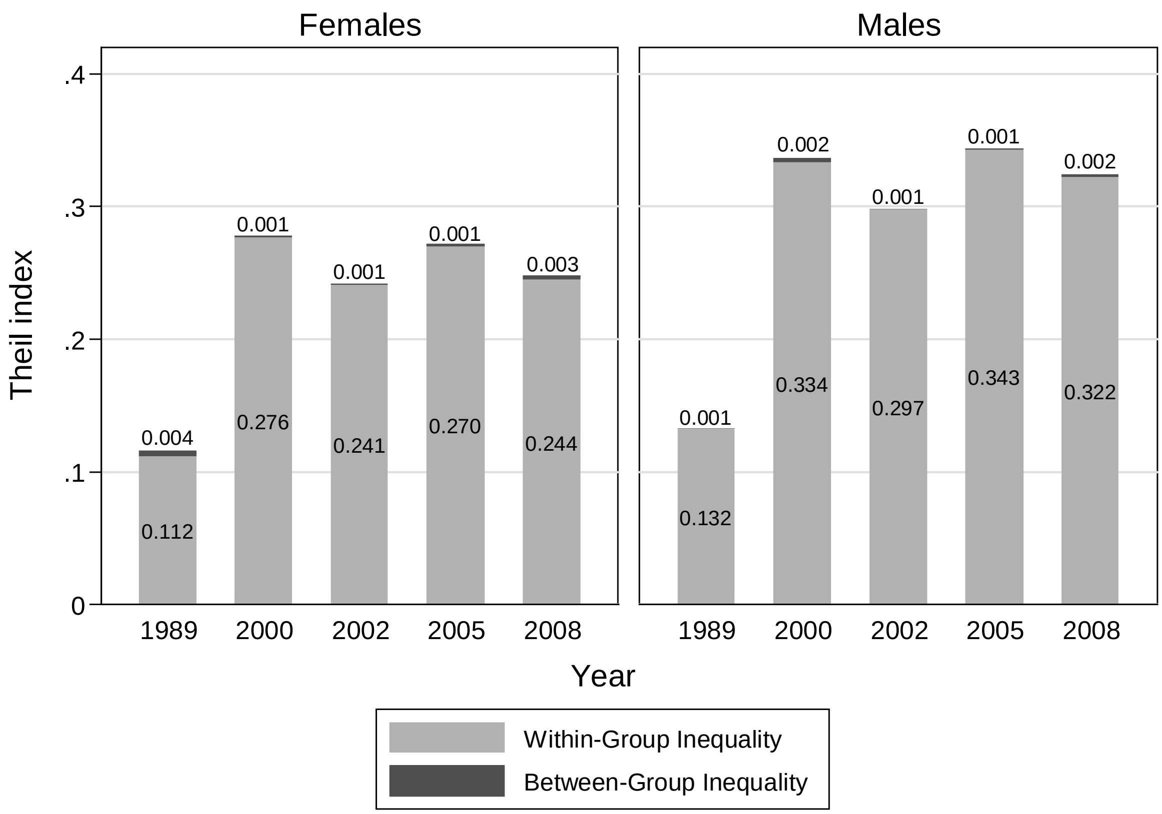
Notes: Results of Shorrocks (1980) decomposition of the Theil index by four subgroups according to highest level of education. The groups are: finished elementary education or less, finished vocational education, high school degree, college/university degree.

Figure 1.14c: Group-Level Mean Wages and Population Shares by Education Groups



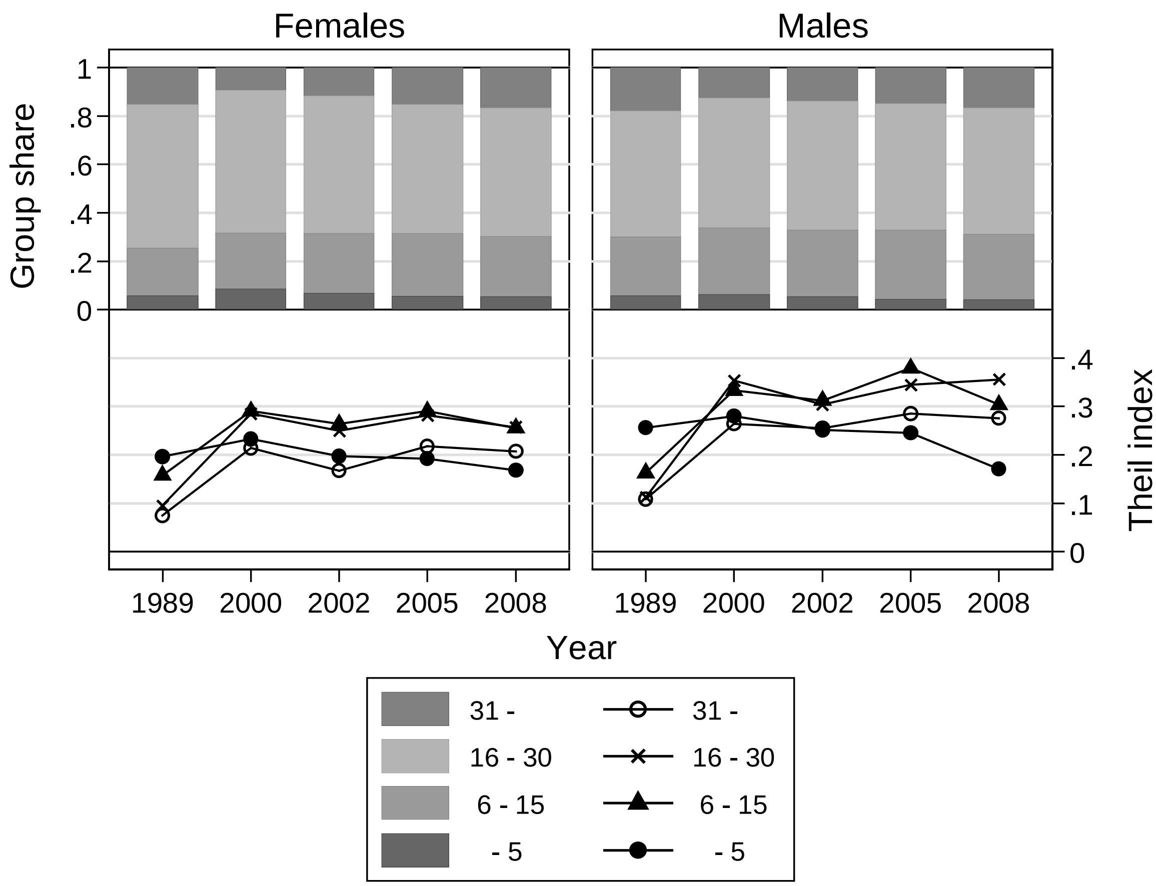
Notes: Results of Shorrocks (1980) decomposition of the Theil index by four subgroups according to highest level of education. The groups are: finished elementary education or less, finished vocational education, high school degree, college/university degree. Mean wages measured in thousands of 2008 Hungarian forints.

Figure 1.15a: Decomposition of the Theil Index by Experience Groups



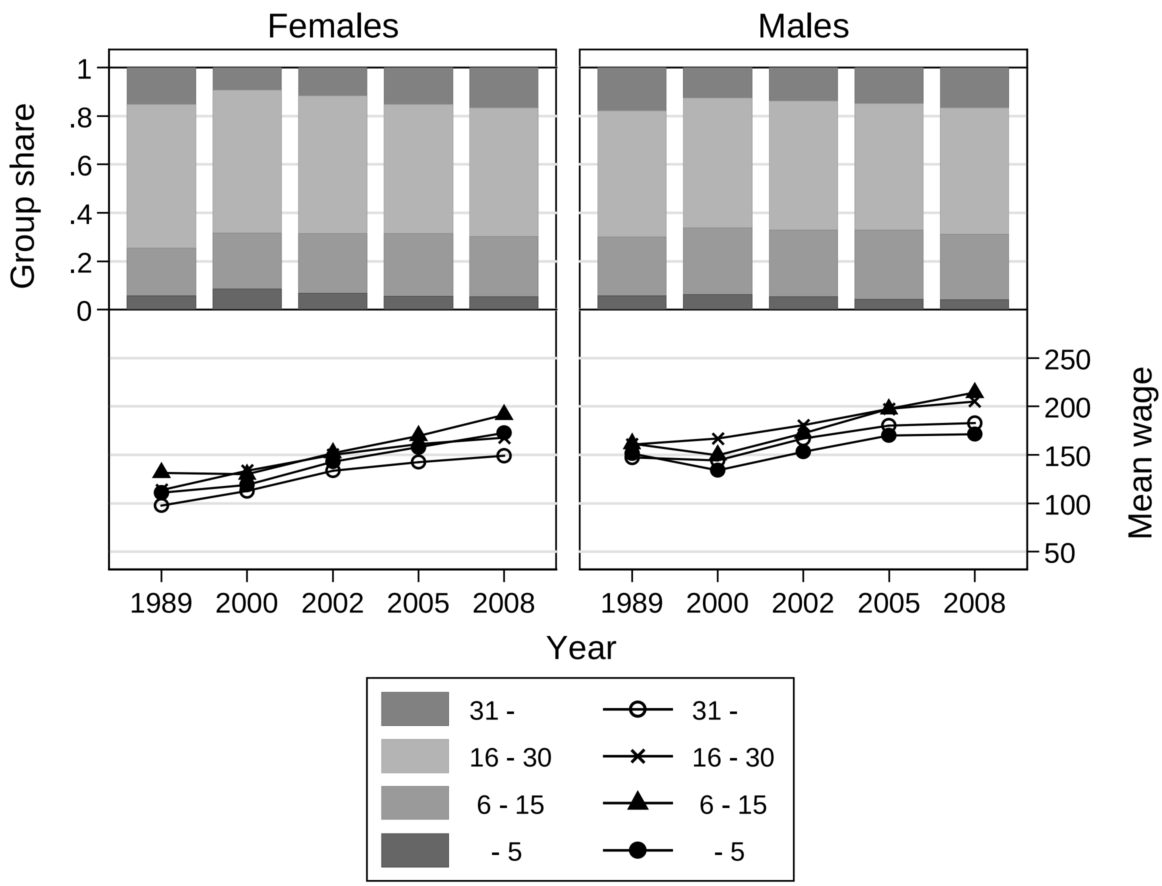
Notes: Results of Shorrocks (1980) decomposition of the Theil index by four subgroups according to potential work experience. The groups are: 5 years of experience or less, 6-15 years of experience, 16-30 years of experience, more than 30 years of experience. Height of bars shown by bar labels.

Figure 1.15b: Within-Group Inequality and Population Shares by Experience Groups



Notes: Results of Shorrocks (1980) decomposition of the Theil index by four subgroups according to potential work experience. The groups are: 5 years of experience or less, 6-15 years of experience, 16-30 years of experience, more than 30 years of experience.

Figure 1.15c: Group-Level Mean Wages and Population Shares by Experience Groups



Notes: Results of Shorrocks (1980) decomposition of the Theil index by four subgroups according to potential work experience. The groups are: 5 years of experience or less, 6-15 years of experience, 16-30 years of experience, more than 30 years of experience. Mean wages measured in thousands of 2008 Hungarian forints.

Table 1.1: Sample Size by Year

	Unweighted		Weighted	
Year	Workers Observed (thousands)	Firms Observed	Workers Represented (thousands)	Firms Represented
1986	542.2	3,679	3,612.0	10,039
1989	366.6	4,063	3,631.2	13,113
1992	83.3	5,683	2,104.4	10,350
1993	81.0	6,008	1,654.7	10,501
1994	102.5	7,845	1,772.1	11,748
1995	104.0	7,948	1,693.4	11,447
1996	100.7	7,521	1,675.4	18,002
1997	100.1	7,518	1,680.5	19,505
1998	101.4	7,437	1,725.8	20,960
1999	102.9	8,027	1,717.1	22,081
2000	121.1	10,255	1,897.3	42,821
2001	122.5	10,910	1,908.0	45,532
2002	123.5	7,874	1,968.4	84,111
2003	119.1	7,396	1,982.0	85,479
2004	132.2	8,304	2,091.1	117,010
2005	140.2	8,483	2,045.0	103,878
2006	129.3	7,934	2,130.0	118,478
2007	127.9	7,529	2,030.8	106,785
2008	125.7	7,639	2,116.0	127,541

Notes: *Workers Represented*: sum of sample weights, *Firms Represented*: sum of firm-level weights. Sample weights are the product of within-firm worker weights and firm-level weights.

Table 1.2: Descriptive Statistics

	1989	2000	2008
Monthly Earnings	140.1	146.3	190.5
	(89.8)	(169.6)	(212.3)
Female (%)	40.8	39.1	38.0
Education (%)			
Elementary	43.1	21.0	15.0
Vocational	27.0	36.8	35.6
High school	24.8	31.6	34.0
University	5.0	10.6	15.4
Experience	22.9	21.9	22.8
	(11.3)	(11.1)	(11.2)
Occupation (%)			
Elementary Occupations	12.2	8.3	8.4
Skilled Manual Workers	49.6	48.9	42.9
Service Workers	6.4	10.2	10.9
Clerks	10.7	6.6	6.6
Associate Professionals	11.8	13.1	15.0
Professionals	5.1	3.9	5.8
Managers	4.4	9.1	10.3
Industry (%)			
Agriculture	25.8	8.5	4.9
Mining	0.9	0.3	0.1
Food&Beverages	7.7	6.6	4.8
Textile	6.7	7.0	2.6
Wood&Paper	2.3	3.3	3.0
Chemicals	2.8	4.4	4.0
Minerals&Water	5.8	6.9	6.7
Machines&Equipment	7.9	13.6	14.0
Utilities	1.4	3.1	1.7
Construction	7.7	6.1	10.3
Retail Trade	9.4	8.7	11.9
Wholesale Trade	4.7	5.3	7.5
F.I.R.E.	1.1	4.9	5.7
Business Services	3.1	5.4	8.6
Other Services	12.7	16.1	14.0
N	366,562	121,051	125,667

Notes: Weighted unconditional means and standard deviations. Earnings measured in thousands of 2008 HUF, deflated by CPI. Standard deviations in parentheses. The definition of occupations follows ISCO-88 where Elementary Occupations, Service Workers, Clerks, Associate Professionals, Professionals and Managers coincide with the corresponding major groups; while Skilled Manual Workers cover Skilled agricultural and fishery workers, Craft and related trades workers and Plant and machine operators and assemblers.

Table 1.3: The Role of the Minimum Wage Increase in Inequality Changes Between 2000 and 2002

Females

Inequality Measure	Change in Inequality: Actual	Change in Inequality: Keeping Minimum Wage Fixed	Percent Explained by Minimum Wage
90-10	-0.258	-0.120	53 (+)
90-50	0.028	0.025	12 (+)
50-10	-0.286	-0.145	49 (+)
CV Squared	-0.158	-0.115	27 (+)
Theil Index	-0.036	-0.018	50 (+)
MLD	-0.040	-0.015	62 (+)
SDL	-0.078	-0.023	71 (+)
Gini Coefficient	-0.031	-0.012	60 (+)

Males

Inequality Measure	Change in Inequality: Actual	Change in Inequality: Keeping Minimum Wage Fixed	Percent Explained by Minimum Wage
90-10	-0.262	-0.142	46 (+)
90-50	0.027	0.025	5 (+)
50-10	-0.288	-0.167	42 (+)
CV Squared	-0.256	-0.210	18 (+)
Theil Index	-0.038	-0.020	47 (+)
MLD	-0.038	-0.011	71 (+)
SDL	-0.067	-0.010	85 (+)
Gini Coefficient	-0.023	-0.007	71 (+)

Notes: Counterfactual values of inequality measures (when minimum wage is fixed at 2000 level) computed from a distribution that would have prevailed in 2002, if the real value of the minimum wage had remained at its 2000 level. Actual distribution of wages in 2002 reweighted below the minimum wage by the method of DiNardo et al. (1996). Above the 2002 minimum wage, the counterfactual distribution and the actual 2002 distribution of wages coincide by construction. Changes given in log points.

Table 1.4a: Changes in Interdecile Differentials of Log Earnings and Percent Explained by Composition Effects

Females

Log Wage Differential	**Period**	**Change in Inequality**			**Percent Explained**	
		Actual	**Controlling for Composition**			
			(1) With Minimum Wage Change	(2) Keeping Minimum Wage Fixed	(1) With Minimum Wage Change	(2) Keeping Minimum Wage Fixed[a]
90-10	*1989-2000*	0.559	0.409		27 (+)	
	2000-2002	-0.258	-0.340	-0.194	32 (–)	62 (–)
	2002-2005	0.154	0.116		25 (+)	
	2005-2008	-0.127	-0.162		27 (–)	
90-50	*1989-2000*	0.248	0.136		45 (+)	
	2000-2002	0.028	-0.017	-0.019	161 (+)	176 (+)
	2002-2005	0.089	0.062		30 (+)	
	2005-2008	-0.084	-0.108		28 (–)	
50-10	*1989-2000*	0.312	0.272		13 (+)	
	2000-2002	-0.286	-0.323	-0.175	13 (–)	21 (–)
	2002-2005	0.065	0.053		18 (+)	
	2005-2008	-0.043	-0.054		25 (–)	

Notes: Counterfactual values of inequality measures computed from a distribution that would have prevailed in the end of the respective period, had the composition of workers at the beginning of the period prevailed. Counterfactual distribution obtained by the reweighting method of DiNardo et al. (1996). [a]For calculations in this column, the benchmark change in inequality is the change adjusted for minimum wage change by the method described in Section 4.2. That is, inequality changes when holding both the minimum wage and skill composition fixed are compared to changes reported in column two of Table 1.3. Changes given in log points.

Table 1.4b: Changes in Interdecile Differentials of Log Earnings and Percent Explained by Composition Effects (cont.)

Males

Log Wage Differential	Period	Change in Inequality: Actual	Change in Inequality: Controlling for Composition (1) With Minimum Wage Change	Change in Inequality: Controlling for Composition (2) Keeping Minimum Wage Fixed	Percent Explained (1) With Minimum Wage Change	Percent Explained (2) Keeping Minimum Wage Fixed[a]
90-10	*1989-2000*	0.659	0.450		32 (+)	
	2000-2002	-0.262	-0.302	-0.174	15 (–)	22 (–)
	2002-2005	0.157	0.113		28 (+)	
	2005-2008	-0.210	-0.224		7 (–)	
90-50	*1989-2000*	0.267	0.161		39 (+)	
	2000-2002	0.027	0.004	0.005	86 (+)	79 (+)
	2002-2005	0.087	0.060		30 (+)	
	2005-2008	-0.046	-0.063		36 (–)	
50-10	*1989-2000*	0.392	0.289		26 (+)	
	2000-2002	-0.288	-0.306	-0.179	6 (–)	7 (–)
	2002-2005	0.069	0.053		24 (+)	
	2005-2008	-0.164	-0.161		1 (+)	

Notes: Counterfactual values of inequality measures computed from a distribution that would have prevailed in the end of the respective period, had the composition of workers at the beginning of the period prevailed. Counterfactual distribution obtained by the reweighting method of DiNardo et al. (1996). [a]For calculations in this column, the benchmark change in inequality is the change adjusted for minimum wage change by the method described in Section 4.2. That is, inequality changes when holding both the minimum wage and skill composition fixed are compared to changes reported in column two of Table 1.3. Changes given in log points.

Table 1.5a: Juhn-Murphy-Pierce (1993) Decomposition of Inequality Changes

Females

Log Wage Differential	Period	Total Change	Contribution of: (in percent of total change) Observable Quantities	Observable Prices	Unobservable Quantities and Prices
90-10	*1989-2000*	0.559	19	34	47
	2000-2002	-0.258	18	28	54
	2002-2005	0.154	23	38	40
	2005-2008	-0.127	17	42	41
90-50	*1989-2000*	0.248	29	35	35
	2000-2002	0.028	375	-146	-132
	2002-2005	0.089	12	60	28
	2005-2008	-0.084	38	33	30
50-10	*1989-2000*	0.312	10	33	56
	2000-2002	-0.286	55	10	35
	2002-2005	0.065	35	11	54
	2005-2008	-0.043	-23	60	63

Notes: Results from decomposition of interdecile differentials according to the residual imputation method of Juhn et al. (1993). Underlying log wage regressions control for education, experience, industry and region. Total changes given in log points. Reference prices and reference residual distribution of the decomposition are average prices and the average residual distribution of the two years, respectively.

Table 1.5b: Juhn-Murphy-Pierce (1993) Decomposition of Inequality Changes (cont.)

Males

Log Wage Differential	**Period**	**Total Change**	**Contribution of:** (in percent of total change)		
			Observable Quantities	**Observable Prices**	**Unobservable Quantities and Prices**
90-10	*1989-2000*	0.659	20	32	48
	2000-2002	-0.262	28	21	51
	2002-2005	0.157	15	28	57
	2005-2008	-0.210	20	36	44
90-50	*1989-2000*	0.267	25	44	31
	2000-2002	0.027	259	-133	-26
	2002-2005	0.087	24	33	43
	2005-2008	-0.046	-28	57	72
50-10	*1989-2000*	0.392	16	23	61
	2000-2002	-0.288	49	7	44
	2002-2005	0.069	3	20	77
	2005-2008	-0.164	34	30	36

Notes: Results from decomposition of interdecile differentials according to the residual imputation method of Juhn et al. (1993). Underlying log wage regressions control for education, experience, industry and region. Total changes given in log points. Reference prices and reference residual distribution of the decomposition are average prices and the average residual distribution of the two years, respectively.

CHAPTER TWO

2. The Effect of Foreign Acquisitions on Wages: Evidence from Hungarian Firm and Linked Employer-Employee Data

(joint with John Earle and Álmos Telegdy)

Abstract

This paper estimates the effects of foreign acquisitions on average and worker-specific wages in previously domestically owned firms in Hungary. The analysis is carried out both at the firm level using universal data for all Hungarian corporations and at the worker level using linked employer-employee data from a very large survey. The panel is much longer (23 years) than in previous studies and the data contain a large number of foreign acquisitions with information both before and after the change in ownership. Our empirical methods include matching on multiple years of pre-acquisition data and fixed effects for firms, detailed worker groups, and individuals (where workers can be linked inside firms). We also exploit reversals in ownership status: acquisition followed later by divestment. While point estimates are sensitive to specification, we find in all cases positive effects of FDI on average wages, and even on wages of all worker types. The only significantly higher foreign premium is associated with university education. We consider possible explanations for the findings, including productivity and rent-sharing, as well as selection and measurement. The evidence suggests that the foreign premium is strongly associated with a similar differential in productivity.

2.1. Introduction

A major finding in recent research using linked employer-employee data is the presence of substantial "employer effects" in wage determination (e.g., Groshen 1991; Abowd, Kramarz, and Margolis 1999; Hellerstein and Neumark 1999). This important result suggests that firms may not merely act passively to convey market forces, and it opens up a broad set of interesting questions: What characteristics of firms are associated with high and low wages? Are the effects of these characteristics neutral across workers, or do they reflect winners and losers among different groups of employees? What factors may explain the observed wage differences across firms – are they due to measurement artifacts, selection bias, unmeasured heterogeneity, or do they represent genuine differences in economic behavior?

This paper addresses these questions with a focus on a particular firm characteristic that has been the subject of controversy in the context of both policy and research: foreign versus domestic ownership. Indeed, the posture of economic policy towards foreign direct investment (FDI), particularly cases of foreign acquisitions, seems to display a certain degree of ambivalence in many countries. On the one hand, FDI is valued as a source of finance, jobs, and technologies, and governments frequently compete for the favor of investors by offering special preferences and tax abatements. On the other hand, most countries completely prohibit majority foreign ownership in so-called "strategic" sectors – for instance, airlines and (until recently) banking in the US – and they often impose additional regulatory burdens and uncertainties that add to the inherently higher costs of sending capital and monitoring managers across national boundaries. These policies are frequently abetted by public fears of globalization, and a major issue in the debates is the effects of foreign ownership on workers and their wages.

Research on wages and FDI has examined a number of countries and used several types of data, and it has consistently documented a positive wage differential in favor of foreign ownership. A major issue in this research, however, is that FDI may be selective, "cream-skimming" or "cherry-picking" the best domestic firms for acquisition and the best areas and industries for greenfield start-ups. Studies using firm-level data have sometimes addressed this problem using fixed effects and matching methods, with the usual result that a smaller foreign wage premium survives (e.g., Conyon et al., 2002, and Girma and Görg, 2007, both on the UK).[36] The firm-level data, of course, typically contain little

[36] Other firm-level studies include Aitken, Harrison, and Lipsey (1996) on Mexico, Venezuela, and the US; Feliciano and Lipsey (2006) on the US; Lipsey and Sjöholm (2004) on Indonesia; and Brown, Earle and Telegdy (2008) on FDI entry through privatization in Hungary, Romania, Russia, and Ukraine.

or no information on individual worker wages and characteristics, which makes it difficult or impossible to control for and analyze employee composition and relative wages by characteristics of workers within firms. Studies of worker-level data with information on employer ownership can address these issues, but they generally do not contain controls for firm selection into ownership type or much employer information, which could be useful for disentangling the possible mechanisms underlying an FDI-wage correlation.[37]

The advantages of both firm- and worker-level data can be exploited only with linked employer-employee data (LEED), and recently there have been several such studies.[38] These studies frequently use fixed effects and matching methods, but unlike the firm-level studies they typically conclude that the causal effect of foreign ownership is small. Wage structure in these studies is usually limited to a disaggregation into only two skill groups, and with few exceptions (discussed below), there is relatively little attention to possible explanations of FDI effects on wages.

Our paper builds on and contributes to this literature in a number of ways. We estimate the impact of foreign acquisitions on the level and structure of wages in Hungary, an economy that rapidly reformed and liberalized inward investment during the 1990s. The data we analyze begin in 1986 when the centrally planned regime completely prohibited foreign involvement, they continue through the adoption of a very liberal regime in which – despite significant opposition – the government awarded special treatment to many foreign investors, and they end in 2008, several years after accession to the European Union. The result of liberalization was ownership transfer from domestic to foreign owners that took place not only quickly but also broadly across nearly all sectors. At the same time, the tightly controlled wages of the centrally planned system were abruptly liberalized, permitting organizations to set their own wages and to increase skill differentials, which had tended to be compressed under socialism (e.g., Kornai, 1990).

The unusually rapid changes in Hungary provide us not only with radically different economic environments in which to estimate FDI effects, but also with two data sets that are particularly suitable for this purpose. The first data set is a comprehensive database covering every formal employer in each year from 1986 to 2008. These data contain close to 5,000 foreign acquisitions with information on wages prior to and after the ownership change, thus useful for identifying ownership effects in the panel. Not only is the number of acquisitions unusually large, but the 23-year long time series are

[37] For example, see Kertesi and Kollo (2002)'s comparison of the returns to education between foreign and domestic firms in Hungary.

[38] See Martins (2004) and Almeida (2007) for Portugal, Heyman et al. (2006, 2007) for Sweden, Huttunen (2007) for Finland, Andrews et al. (2007) for Germany, and Martins and Esteves (2008) for Brazil.

invaluable, providing in most cases several years of pre- and post-acquisition information.[39] These data contain detailed information on firm-level financial and performance measures, including firm-level labor costs from which we compute average monthly wages per worker.

The second data set links worker-level information with a sample of the firms, thus forming a linked employer-employee database (LEED) for the years 1986, 1989, and each year from 1992 to 2008. Within these data there are fewer ownership changes – 647 – but still more than in most studies of FDI and wages, and there are large numbers (almost 2 millions) of worker observations within these firms before and after the ownership change. The LEED includes individual worker wages and worker characteristics, allowing us to control for the composition of workers around the ownership change and to study the heterogeneity of the foreign wage premium by schooling, age, gender, occupation, and some partial measures of job tenure. Two drawbacks of the worker data are that they are a sample (although one that is clearly random), not the population, and that there is no unique identifier that would allow construction of a consistent panel. The available worker characteristics are detailed enough, however, for us to be able to follow most workers from one year to the next if they remain with the same employer.

Our empirical strategies exploit the richness and size of these data in several ways. We focus on acquisitions both because of their particular interest in the political economy of FDI (greenfield investments tend to be less controversial) and because of the better possibilities of identifying their effects in the panel data. Throughout, we exploit the full longitudinal structure of the data, rather than selecting arbitrary pre- and post-acquisition years. To construct matched control groups for acquired firms, we use detailed financial data, including wages, over several years. By contrast, most previous studies of FDI and wages are restricted by the available data to use information only from the year of acquisition or the year just before for matching. We combine matching with regression, including firm fixed effects to account for time-invariant heterogeneity across firms or fixed effects by types of worker within firms, based on cells defined by gender, educational category, number of years of experience, and county in each firm (which produces about 400,000 cells with at least two worker observations in a total sample size of 1.9 million). Moreover, by linking individual workers over time within firms, we can include worker-firm fixed effects, which help in identifying the impact on incumbent workers at the time of takeover.

We carry out these analyses with both the firm-level data, which has the advantage of large numbers of observations and complete coverage, and the LEED, which has the advantage of

[39] In most previous studies, the length of the entire panel is 5 years or less, and the number of ownership switches is typically between 100 and 300. Studies with more switchers usually have few observations per treated firm (acquisition or divestment) both before and after treatment.

information on individual workers. Our purpose, moreover, is to shed some light on an important and somewhat neglected issue in analyzing the relationship between worker wages and firm characteristics: the question of whether the appropriate unit of observation is the worker or the firm.[40] Analyzing workers exploits the variation in wages among workers and allows their characteristics to be controlled for, so that the (observable) composition of employment is held constant. Analyzing firms is appropriate because ownership is an attribute of the firm, and it may be advantageous if the firm-level wage is better measured than wages at the individual level, for instance in the case of incomplete sampling of workers, such as in our data.

In a further extension of this empirical strategy, we take advantage of the presence in the data of cases where a Hungarian firm is acquired by a foreign investor but later divested into domestic Hungarian hands. If FDI has a causal effect on wages that our methods enable us to identify, then one might expect the estimated acquisition and divestment effects to be roughly symmetric – similar in magnitude but opposite in sign. A strong violation of symmetry would raise questions on whether a causal effect has been identified; at least, a more complicated story would be required to account for a foreign effect that persists long after a divestment. Our symmetry test is particularly strong, as it involves ownership switches within the same firm, thus removing any systematic, time-invariant, unobservable differences between acquisitions and divestments. As an example, if we were to find that the acquisition effect is positive and the divestment effect is zero, a possible interpretation is that acquisition coincided with other factors that led to higher wages, but the role of FDI may have been purely incidental. Alternatively, this result could be consistent with a permanent effect of FDI working through new technologies or better worker selection (controlling for observable characteristics). But we would not be able to distinguish these different interpretations. On the other hand, if we find that acquisition results in higher wages and divestment returns them back close to their original level, then the case for a causal interpretation would be strengthened.

Using these methods, we find consistent evidence of a positive impact of foreign acquisitions, in our preferred specifications generally lying in the range of 10 to 30 percent. This range is similar to standard estimates of the wage effects of trade unionism (e.g., Pencavel 1991). When we focus on firms with acquisition followed by later divestment, we find, particularly for the matched samples, that divestment largely reverses the acquisition effect. The wage premium in acquired firms therefore seems to result from the characteristics of the owner, rather than from the acquisition process or the nature of the target.

[40] See Pencavel (1991) for a discussion of this issue in the context of trade unions and Earle and Telegdy (2008) using the example of privatization.

Moreover, when we permit the wage effect to vary by worker characteristics – gender, experience, education, new hire, and occupation – the results imply that FDI raises wages for all groups of workers (defined for each of these characteristics separately: i.e., men vs. women, different experience groups, etc.). Even incumbent workers realize a significant wage gain, and while that estimate is conditional on continued employment in the firm, we find only small impacts on the observable composition of workers. A higher wage premium in acquired firms is consistently estimated only for university-educated workers, but we are unable to identify any groups of "losers;" rather, all types of workers (in the single-characteristics sense) appear to be "winners."

Given these results, we organize a further analysis of the patterns of FDI effects around a search for possible explanations, including measurement and selection issues, and mechanisms working through enhanced productivity, rent-sharing, and personnel policies. To address these issues, we rely on detailed information on both the worker side, where we can disaggregate the FDI by skill and other characteristics, and the firm side, where we can use information on firm performance.

The next section describes the construction of our database, and in Section 3 we briefly explain the evolution of the ownership structure and provide summary statistics for wages and characteristics of firms and workers. In Section 4 we describe the details of the estimation procedures. Section 5 presents the results of our estimates of average FDI effects, and Section 6 examines a number of explanations of the foreign wage premium. Section 7 concludes with a summary and suggestions for further research.

2.2. Data Sources and Sample Selection

We analyze data from two sources. The first is the National Tax Authority in Hungary, which provides balance sheet data for all legal entities engaged in double-entry bookkeeping. Comparison with the total number of companies by legal form from the Statistical Yearbooks of Hungary 1992-2008) reveals that essentially every formal sector employer is included in the data if the company is of limited liability (Ltd or joint stock), while the proportion of included partnerships gradually increases as the regulation changed and required them to engage in double-entry bookkeeping. In early years only about 20 percent of such firms are present, while by the end of the period almost all of them are included. As foreign investors rarely acquired partnerships, our data can be considered universal with respect to the studied question. The data are available annually from 1992 to 2008 for all firms and from 1986 to 1991 for a sample which is biased towards large enterprises. The data thus provide information for a long period which starts well before the transition started and ends several years after the country's accession to the European Union. The firm-level data files include the balance sheet and income statement, the proportion of share capital held by different types of owners, and some basic variables, such as employment, location and industrial branch of the firm. These data have been previously studied and are further described by Brown, Earle, and Telegdy (2006, 2010).

The second source is the Hungarian Wage Survey, hosted by the National Employment Office, which has information on workers' earnings and characteristics every three years between 1986 and 1992, and on an annual basis ever since. In this study we use the time series through 2008. The survey requires firms to send information for a sample of their employees. In 1986 and 1989 the survey covered all firms. As at the start of the transition a vast number of small firms entered the economy, the sample design was changed to having only firms with more than 20 employees. This size threshold was kept until 1995; next year a random sample of smaller firms was added. For the period between 1996 and 1999 employers with 11-20 workers were included while for the last period the lower sampling threshold was reduced to 5 employees.

In 1986 and 1989, workers were selected from narrowly defined occupational and earnings groups within firms, using a systematic random design with a fixed interval of selection. High-rank managers were exempt from this rule and were surveyed comprehensively. In 1992 the sample design changed and was based on the day of birth of workers. Production workers were selected if born on the 5th or 15th of any month, while non-production workers were chosen if born on the 5th, 15th, or 25th of any month. Therefore, even though the target group of the survey was the population of firms above 20 employees, if a firm did not have any employees born on the given days in a particular year, the firm-year is missing from the data. This design was maintained for the firms with at least 20 employees by 2001, and for firms with employment above 50 thereafter, but for the smaller firms all employees' information was required. This selection procedure results in a random sample of about 6.6 percent of production workers, and 10 percent of non-production workers. We use information on the numbers of production and non-production workers in the firm to weight the within-firm samples and adjust for the oversampling of non-production workers. Since a firm drops out from the sample if none of its employees were born on the relevant dates, the probability of being included increases with employment size of the firm.[41] To overcome this problem, with the help of the comprehensive firm level data described above we also construct a firm weight which varies by firm size and adjusts the sample to the total number of employees in the relevant sectors of the Hungarian economy.

The Wage Survey data provide extensive information on employees' earnings (discussed in detail in the next section) their highest level of education, gender, age, occupation, whether the worker

[41] For example, a firm with 20 production workers will have a probability of 0.11 to be excluded from the sample, while for a similar firm with 100 employees this probability is only 0.012.

is a new hire and working hours in some years.[42] The data also include a sufficient set of firm characteristics to link the worker records to firm-level data. The result is a linked employer-employee dataset (LEED) in which we are able to follow firms through a consistent firm identifier; however, workers are not organized in a panel and thus cannot be followed in time. Nonetheless, relying on the abundance of individual information and on the sampling scheme being based on birth date, we linked 44 percent of observed employees that do not change their workplace from one year to the next. Although we cannot identify the effect of ownership change from workers who move between domestic and foreign firms, we can control for unobserved worker heterogeneity in case of employees that stay with the same firm during a foreign acquisition or divestment.

We cleaned both the firm level and individual datasets extensively. In particular, we cleaned firm ownership data, checking for miscoding and dubious changes. We also cleaned the longitudinal linkages of the data. For this procedure we used a dataset by the Hungarian Statistical Office that provides information on re-registration and boundary changes, which result in spurious entry and exit of firms from our data. As this dataset is not comprehensive, we also detected false entries and exits by looking for matches of exits among the entries on the basis of headquarter settlement, industry, sales, and employment. While we know that spurious entry and exit is still a potential source of bias in our data, we believe we decreased the magnitude of this problem to a large extent.

In the firm-level data we also cleaned unbelievable data entries for some continuous variable (employment, wage bill, and sales). If the value of the variable increased (decreased) at least 8 times and then decreased (increased) back, we set the middle year's value to missing. This procedure affected 6,200 employment figures, 600 sales and 40,500 wage bill data points (the total number of firms years in the data is 615,000). In the case of employment, we checked the time series manually and if it were possible, we imputed the value in the middle year (2,200 cases). In the case of the wage bill we set it to missing if the average wage in a firm in a given year was less than the minimum wage

[42] We work with a five-degree scale of education: *Elementary* includes individuals who completed at most a primary school which means in the Hungarian system that they typically have eight or less years of schooling; *Vocational* includes workers who completed a vocational school, but did not take a general high-school-leaving examination (corresponding typically to 10 or 11 years of schooling); *High School* covers individuals who graduated from high school – either from a general or a specialized high school, the latter giving a specialization as well – plus individuals who completed at most two more years of specialized post-secondary education (corresponding on average to somewhat more than 12 years of schooling); and *University* groups individuals with at least a college or university degree (corresponding on average to close to 16 years of schooling).
Occupation is given at the four-digit level following the ISCO-88 classification, of which we aggregate to seven broad occupational groups: *Unskilled* covers elementary occupations (ISCO major group 9); *Skilled Manual* includes skilled agricultural and fishery workers, craft and related trade workers, and plant and machine operators and assemblers (ISCO major groups 6,7,8); *Service* includes service workers and shop and market sales workers (ISCO major group 5); *Skilled Non-Manual* includes clerks (ISCO major group 4); *Associate Professionals* (ISCO major group 3); *Professionals* (ISCO major group 2); and *Managers* (ISCO major group 1).

(16,000 firm-years). If the sales figure was missing in a given year, we imputed it as the average of the sales figure in the two adjacent years if the difference in the two adjacent years was not more than 10 percent (6,900 firm-years). The number of firm-years with imputed numbers dwarf compared to the total number of firm-years in the data.

Finally, since our data span more than two decades during which radical changes took place in the Hungarian political and economic system, we paid a great deal of attention to harmonizing variable definitions and classifications over time. In particular, we harmonized both pre-transition and post-transition industry codes at the two-digit level to the common classification used in Hungary between 1992 and 1998 (called *TEAOR '92* it is a system almost identical to the ISIC classification); we harmonized the highest degree of education to the five-degree scale described above; and we translated socialist occupational and legal form codes to post-transition codes that are consistent with Eurostat norms.

From the LEED we selected those firms which were above the respective size threshold of sample inclusion in a particular year (the sample was reduced by 3800 firms and about 12,000 workers).[43] We also drop 792 companies that went through more than two changes in majority ownership during their presence in the dataset even after extensive cleaning, the reason being that ownership information of these firms seems to be implausible. We restrict our attention to full-time employees only, and – following ILO standards – we focus our attention to individuals between the age of 15 and 74.

Our final selection rule is to drop firms from those two-digit industries where no foreign acquisitions took place.[44] After further minor decreases due to missing values, the resulting firm-level sample comprises 1.9 million firm-year observations on 377 thousand unique firms, to 33 thousand of which we link employee information resulting in a LEED of 2.5 million worker-years. Table A2.1a gives detailed information on the number of non-missing observations per year in the firm-level sample, while Table A2.1b shows numbers of workers with full information on individual characteristics, and numbers of firms with information on ownership and location. The last column in both tables aggregates sample weights and thus indicates the magnitude of total employment in the corporate sector that our sample represents. As mentioned earlier, we only observe a sample of firms even in the firm-level data before 1992, but after that the unweighted numbers in Table A2.1a

[43] These are probably firms that passed the threshold of inclusion between the time of the sampling and sending the questionnaires. We drop these because there are very few firms in these size categories and the firm weights would be very large (as they are defined by size groups).

[44] The following industries (by the NACE classification) were excluded from the analysis: 12, 13, 42, 91, 95, 99. This procedure reduced the firm-level sample by 828 firm-years.

approximate the universe of double-entry bookkeeping enterprises that filed their financial reports to the Tax Authority. Except for the first two observed years, in each year the number of workers in the LEED is between 73 and 112 thousand, making a random sample of 3,673 firms in 1986, 6,595 in 1997, and 6,324 in 2008. Both of our samples represent a total employment of more than 3 million in pre-transition years, and around 1.5-1.7 million after the transition.

We rely on an additional source of information for a subset of acquired firms. Searching the database of the Hungarian Ministry of Public Administration and Justice (MPAJ) on operating enterprises, we gathered information on the country of origin of foreign investors in case of those firms for which the firm identifier used by the MPAJ was available in the dataset. In general, the main identifier in our firm-level data is different from the MPAJ identifier, but for around ten percent of all firms the MPAJ code is also recorded. For about 700 acquisitions – of 4,928 in total – we managed to identify the origin of the acquirer and in most cases we can follow changes in the country of origin of the main foreign owner throughout the post-acquisition history of the firm. We use this information in one of our specifications to identify differential wage effects of FDI from different source countries.

2.3. Ownership Evolution, Variable Definitions, and Summary Statistics

Hungary got off to an early start in corporate control changes with gradual decentralization and increased autonomy provided to state-owned enterprises during the late 1980s (Szakadát, 1993). The first foreign acquisitions took place already in 1989, the most well-known being the privatization of the lighting company Tungsram, bought up by General Electric. In the early 1990s not only were constraints on foreign investment drastically eased, but tax and other preferences for foreign investors were also provided (Organization of Economic Cooperation and Development, 2000). By the mid-1990s, Hungary had the highest value of foreign direct investment per capita among the post-socialist countries (King and Váradi, 2002).

Our database provides information on the ownership shares of domestic and foreign owners at the end of each year (the reporting date), which we use to construct the dummy variable of foreign ownership. The share distribution of acquisitions driven foreign ownership in 2000 is shown in Figure 2.1.[45] Almost one-third of the firms with positive foreign ownership are fully foreign owned and 20 percent possess exactly 50 percent of the company's shares. The other firms are distributed roughly equally around all possible ownership stakes.

[45] Except for several years at the beginning of the time period observed in the data, the share distribution of foreign ownership is very similar to the one presented here in each year.

We define a firm as foreign controlled if a majority of its shares are in foreign hands. Alternative thresholds (e.g., 10 percent) would change little the set of firms classified as foreign, but they do the timing of foreign acquisitions to some extent, because foreign owners sometimes buy firms up gradually.[46] The evolution of the foreign acquisitions in our two samples, as well as the total employment of these firms is presented in Figure 2.2, which clearly reflects the early start and the importance of foreign acquisitions in shaping Hungarian corporate ownership. In the comprehensive firm data the proportion of foreign acquisitions started to increase already in 1990 and quickly reaches 3 percent, their aggregate employment being as much as 15 percent of all employment in the firm-level data in 1999. After this year their share in employment fell but nevertheless remained as high as 12 percent. The proportion of foreign-owned firms in the LEED sample is much larger – around 17 percent after an initial increase – which is due to the fact that this sample does not contain microenterprises. The total weighted employment in this sample has the same proportion of foreign ownership as the comprehensive data.

These firms become foreign-owned as a result of a large number of acquisitions involving foreigners, as Table 2.1 shows. In the comprehensive data there are 4,928 foreign acquisitions, much more than any studies could work with before. In the LEED the number of ownership switches is much smaller – 647 – but still larger than in most of the studies analyzing foreign ownership. Many of these acquisitions are single, meaning that the firm becomes foreign-owned and does not change ownership status again. A significant number, however, is divested by the foreign owners and they become domestically owned again, which we use in our identification method as we will discuss in the next section. There are 983 and 87 such firms in the firm and the linked data, respectively. Not only the number of acquisitions is large, but the time series before and after the acquisitions are long enough to estimate a causal effects of foreign ownership. Table A2.2a shows that the average length of years before single acquisitions is almost 4 in the firm level data (and 3 in the case of acquisitions followed by a divestment) while the average length of the time series after the acquisition is even longer by more than one year. The length of time series in the LEED are very similar to the firm level's as shown in Table A2.2b.

The only condition a firm has to satisfy to be a foreign acquisition or divestment is the passage of the 50 percent threshold, but firms may differ substantially in the starting and ending proportions of foreign ownership. We look at the foreign share distribution in such firms to analyze which is the typical ownership change: does the foreign ownership stake change only several percentage points

[46] We ran the regressions with the foreign dummy defined around the 10 percent threshold and the results changed very little.

around the 50 percent threshold or foreigners rather buy and sell large proportions of capital in such firms? This question is important from a corporate governance perspective, as firms which already have substantial foreign ownership before the acquisition (or after divestment) and they keep domestic ownership after acquisition (or have such owners before divestment) are likely to have smaller changes in behavior than those which abruptly change their foreign stake from nothing to full foreign ownership (or in the opposite way in the case of divestments). We analyze the foreign ownership stakes before and after acquisitions and divestments in Figure 2.3. The bars show the distribution of firms by the pre-acquisition (divestment) foreign ownership share, and the diamonds show the proportion of foreign ownership after the change in ownership had taken place. The pre-acquisition share information reveals that 70 percent of the target firms did not have any foreign ownership. 20 percent of all firms had 50 percent owned by foreigners before the acquisition while the remaining 10 percent of firms are distributed roughly equally across other proportions of pre-acquisition foreign ownership. After the foreign takeover, foreign ownership share is very high, reaching 80 percent on average. Divested firms show similar ownership patterns: almost 60 percent of them were only foreign-owned before the divestment and the average foreign ownership stake after the divestment is much less than 10 percent. In summary, a large part of the ownership switches result in extreme changes in foreign ownership.

We use different wage definitions in the comprehensive firm data and the LEED. As most of the previous studies, in the firm data we use the firm-level average wage, defined as the total payments to workers (not including the payroll tax and non-pecuniary benefits) over the average number of employees.[47] Wages are deflated by yearly CPI and are measured in 2008 Hungarian forints. The first row of Table 2.2 shows that unconditional mean wages are twice as large in single acquisition firms as in the domestic enterprises, while the gap is about sixty percent in case of acquired firms that are later divested.

The LEED have information on individual wages paid in May. They include the monthly base wage, overtime pay, regular payments other than the base wage (such as language and managerial allowances), and 1/12th of the previous year's irregular payments (such as end-of-year bonuses). If the worker was hired during the previous year, we divide the last wage component by the number of months the worker spent with the company in that year. Table 2.3 shows that by this measure the wage premium in firms acquired is similar to the figure in the firm level data.

[47] We prefer this definition over the one using the total wage cost for comparability reasons with the individual wages, used in the analysis of the LEED database.

Besides wages, Table 2.2 also presents the characteristics of firms while Table 2.3 provides the descriptive statistics for worker characteristics. Measured by the value of tangible assets or employment, foreign firms are much larger and they are also much more productive (as measured by labor productivity, defined as the value of sales over the average number of employees). There is a clear difference though between the two groups of foreign firms: those that get back to domestic hands are on average smaller and less productive. The industrial composition of foreign and domestic firms also differs substantially. Relative to domestic firms, foreign-owned firms predominate manufacturing, and they are less prevalent in agriculture, construction, business services and other services than those separately considered. In summary, foreign-owned firms are larger, more capital-intensive and more productive than domestic firms, and they are concentrated in trade and manufacturing.

The average characteristics of workers also vary by ownership type. Foreign owners employ a higher proportion of female workers and university graduates; vocational and high school graduates are in similar proportions employed in domestic and foreign companies and those with only elementary education are more likely to be employed by domestic firms. Employees have similar length of work experience and the same likeliness to be newly hired.[48] The occupational distribution differs between foreign and domestic firms: the workforce in foreign-owned companies has a higher proportion of associate professionals and professionals, smaller proportions of workers in elementary occupations, service workers and clerks while the proportion of managers is the same across the two ownership types. Relative to domestic firms, therefore, workers in foreign companies tend to be more educated, female, somewhat less experienced, and more likely to be in professional and associate professional occupations. The firm and worker characteristics, of course, are simple unconditional means that take no account of any other characteristics of foreign and domestic companies, but they are suggestive of the underlying heterogeneity in the population.

2.4. Estimation Procedures

2.4.1. Estimation equations, panel data treatment of selection

We follow the broader literature on the effects of ownership in estimating reduced form equations, while trying to account for potential problems of heterogeneity and simultaneity bias (Djankov and Murrell, 2002; Megginson and Netter, 2001). We are able to exploit the longitudinal structure of the data as well as the rich set of worker characteristics in order to estimate panel

[48] The new hire variable equals 1 if the worker was hired during the previous year. Since wages are for May in LEED, this variable does not capture the new hires in the given year between January and May, and it adds to the bulk of new hires those who were hired during the same period in the previous year. When we only used the linked worker data, we define new hires as those who were not present in the data in the previous year.

regressions with several types of fixed effects and to construct matched samples that include a set of control firms similar to those acquired by foreigners. We combine matching and difference-in differences estimation techniques in a number of specifications, and to focus on the impact of FDI on incumbent workers we employ worker fixed effects in a subsample where workers can be linked.

Our first firm-level estimating equation describes the foreign differential controlling only for region and year:

$$(1) \qquad lnWjt = \alpha + \delta fFOREIGNj,t\text{-}1 + \Sigma\gamma jREGIONj + \Sigma\lambda tYEARt + ujt,$$

where j indexes firms and t indexes time. lnW_{jt} is the natural logarithm of the wage bill per employee, and we control in each specification for 23 year effects (*YEAR*) and 7 regional effects (*REGION*).[49] u_{jt} is an error term of which we make several assumptions as described below.

In our baseline specification estimated on the LEED sample we run Equation (1) at the worker-level. In particular:

$$(2) \qquad lnw_{ijt} = \alpha + \delta_f FOREIGN_{j,t\text{-}1} + \Sigma\gamma_j REGION_j + \Sigma\lambda_t YEAR_t + v_{ijt},$$

where now i indexes workers, j indexes firms and t indexes time. lnw_{ijt} is the natural logarithm of individual monthly earnings and v_{ijt} captures unobserved components of individual wages.

The variable *FOREIGN* is a dummy variable that takes the value of one if the firm is controlled by foreign owners. As ownership is measured at the end of each year, our ownership variable is lagged. In a set of specifications we disaggregate *FOREIGN* into two types of foreign acquisitions: single acquisitions and acquisitions followed later by divestment (i.e. a domestic acquisition) after at least one year of foreign ownership. The control group is comprised of always domestic firms. Because we observe different ownership histories, we are able to identify the effect of foreign ownership on wages from two sources of variation: from firms in domestic ownership acquired by foreigners and from foreign firms that are later divested to Hungarian investors.

To account for possible differences in workforce composition which may be correlated with ownership, we take advantage of worker information, and we augment equation (2) with controls for gender and human capital:

$$(3) \qquad lnw_{ijt} = \alpha + \boldsymbol{X}_{it}\boldsymbol{\beta} + \delta_f FOREIGN_{j,t\text{-}1} + \Sigma\gamma_j REGION_j + \Sigma\lambda_t YEAR_t + z_{ijt}.$$

[49] An alternative control for non-random shocks would be to interact region and year in order to permit these shocks to vary over both dimensions simultaneously. In our data, this would imply adding 160 dummies instead of 28, which would make some of our computations very time consuming. Nevertheless, we ran most of our specifications including the full region-year interactions, and the results were little changed.

$\boldsymbol{X}_i$ is a vector of individual characteristics including three educational dummies (*VOCATIONAL*, *HIGH SCHOOL*, and *UNIVERSITY*, the omitted category being at most 8 years of schooling), (potential) *EXPERIENCE* in level and squared, and a dummy variable for gender equaling one for female employees (*FEMALE*). As education and experience may be correlated, and gender may influence both, we include a full set of interactions among these variables.

In an additional specification, we add dummy variables indicating broad occupational categories and whether the worker was newly hired in the past year, to control more precisely for the composition of the workforce. However, due to the potential endogeneity of occupation, in most of the analysis we only control for education, gender, experience, and their interactions. Finally, we also check how the industrial composition of firms changes the wage effect as a consequence of possible correlation between inter-industry ownership distribution and industrial wage differentials.

As discussed in the previous section, we distinguish two types of foreign acquisitions in the data: single acquisitions and those which are followed by a divestment to domestic owners. To test for the difference between these two types of acquisitions and to analyze what happens to wages after the foreign-owned firm is divested, we disaggregate *FOREIGN* into a dummy indicating single acquisitions, another one indicating that the acquisition was followed by a divestment, and a divestment dummy. The estimating equation is the following:

$$(4) \qquad lnW_{jt} = \alpha + \delta_{f1}FOREIGN1_{j,t-1} + \delta_{f2}FOREIGN2_{j,t-1} + \delta_d DIVEST_{j,t-1} +$$

$$+ \Sigma\gamma_j REGION_j + \Sigma\lambda_t YEAR_t + u_{jt},$$

where δ_{f1} shows the effect of foreign ownership for single acquisitions, δ_{f2} of those followed by a divestment and δ_d shows the wage effect of divestments. This equation can also identify the symmetry of the foreign effect: does the wage effect fall after the divestment, or it remains at its previous level?

We fit these equations under alternative assumptions about the error terms, u_{jt}, v_{ijt}, and z_{ijt}, first assuming that the disturbance is uncorrelated with each right-hand-side variable. We use this simple OLS as a benchmark for examining other specifications that can more seriously claim to estimate causal effects, under alternative assumptions about firm and worker heterogeneity.[50]

In other specifications we try to account for non-random selection of firms into ownership type: the owners of the acquiring firms are likely to select targets that have better growth prospects or a more skilled workforce, for example. If this aspect of the firm is not observed for the researcher, the

[50] We report all standard errors permitting general within-firm correlation of residuals using Arellano's (1987) clustering method. The standard errors of all our test statistics are robust to both serial correlation and heteroskedasticity. See Kézdi (2004) for a detailed analysis of autocorrelation and the robust cluster estimator in panel data models.

estimated effect of ownership on wages will be biased if estimated by OLS. To account for this selection bias, we first add firm fixed effects to the regression to control for all unobserved time invariant effects at the firm level.

Unobserved heterogeneity may vary not only at the firm level but also within groups of workers in the same firm, so in another specification we interact the firm fixed effect with narrowly defined groups of workers. They are defined by gender, four education categories, and years of experience. We also distinguish workers by county (which is defined at the plant level) and the resulting grouping is interacted with firm identifiers. In this specification therefore we allow a different intercept for each education-gender-experience-county group within each firm. This procedure results in adding about 400,000 worker-firm fixed effects to the regressions.

2.4.2. Matching procedures

The universe of domestically owned firms may be very different from those which are owned by foreign investors. To construct a control group as similar as possible to the group of acquired firms, we apply propensity score matching (Rosenbaum and Rubin, 1983). As acquisitions are applied to firms, we also match on firm, rather than worker characteristics.

We use in the matching only those acquisitions which have observations on average wages one and two years before the treatment took place. As potential controls we also use only those always domestic firms which satisfy this requirement relative to the year when we add them among controls.[51]

To obtain the propensity score, we run a pooled probit on the treated firms and potential controls, with the dependent variable equal to one if the firm was acquired in a given year, and zero for domestic firms' years when they satisfied the inclusion criterion. We prefer pooled estimation to the by-year estimation of the propensity score because the relatively small number of treated firms would make the regressions less robust. In order to account for the high number of potential control firms compared to treatments, we compute in every year the ratio of treated firms to the number of potential control firms, and we use this proportion to downscale the controls in the probit regression (treated firms receive a weight of one). Independent variables include the logarithms of the level and square of average earnings, employment, labor productivity (value of sales over employment), capital intensity (value of tangible assets/employment) one year before acquisition; wage and employment growth from two years before acquisition to one year before acquisition; and industry and year effects. It is

[51] For example, a domestic firm can be included among the potential controls for firms acquired in 1993 if it has information on its average wage in 1992 and 1991 and one year after 1992. As acquisitions happen not in a single period but along multiple years, the very same firm can also be included in the set of potential controls in 2005 if it has non-missing average wages in 2004 and 2003 as well as on one year after 2004.

important to note that by including pre-treatment levels and growth of wages among the regressors, we not only match on observable, but on unobservable characteristics as well.

We report marginal effects from the propensity score estimation in Table A2.3. In general, the direction of the effects of explanatory variables is the same in the two datasets, although none of the estimated coefficients are significant at the five percent level in the LEED where sample size is smaller than in the firm-level sample. Bigger firms with higher average wages, higher productivity and higher capital intensity are more likely to be acquired.[52] Faster growing companies are also more often acquisition targets, while wage growth does not seem to have a significant influence on investors' decisions and the point estimate is negative in contrast with the effect of the level of wages.

Having obtained the propensity score, we enforce common support of its distribution across treated and control firms by dropping the treated (control) firms which have larger (smaller) propensity score than the largest (smallest) score obtained for control (treated) firms. Then, on the common support we perform exact matching by industry and year; in every industry-year cell we match to each treated firm its nearest neighbor measured by the propensity score. We match with replacement so an always domestic firm may be matched to more than one treated firm. To check the quality of our matches, we compute normalized mean differences in the matching variables between the treated and the control group one year before acquisition. Table 2.4 shows that differences are very low, none of them exceeding 0.1.[53]

We end up with 1,756 matched treated firms in the firm-level sample, and with 476 pairs in the LEED. Table 2.5 provides detailed information about the distribution of acquisitions over time which is quite uniform except for the very early and very last years, where pre- and post-treatment information requirements restrict the sample. Table 2.6 compares some characteristics of firms that are included in the matched samples to all firms in the full samples. Matched companies are on average much larger and more productive, pay higher wages and are more likely to operate in manufacturing relative to the typical firm in the data. Thus, we expect results obtained from regressions on the matched sample to be different from estimation results in the full samples. We will analyze this difference more carefully in the results section.

Investigating firm-level descriptive statistics of matched enterprises by ownership type in Table 2.7, we find that wages, size and productivity of domestic and acquired firms are much closer on

[52] Note that in the firm-level sample, for companies with very small average wages and very few employees the marginal effect of wages and employment is even negative. The cutoff point is 4.6 employees and 36,000HUF per employee per year. The latter value is practically not binding since it is less than the smallest value of the monthly real minimum wage over the sample period.

[53] Imbens and Rubin (2010) suggest that as a rule of thumb, differences below 0.25 are acceptable.

average than in the full samples (see Table 2.2), moreover, always domestic firms are bigger and more productive than acquired but later divested firms, and in the firm-level sample they even pay higher wages. Nonetheless, acquired firms that are not resold still have a wage premium unconditionally. In what follows, we will examine the magnitude of the conditional acquisition wage premium.

In Table 2.8, we report descriptive statistics at the individual level on earnings and the composition of workforce in the matched sample. Just as in the case of firm-level average wages, the raw difference between average individual wages in foreign and domestic firms is smaller than the gap reported in Table 2.3 for the full sample. Moreover, both matched domestic and matched acquired firms pay higher wages than the respective average in their own group in the full data. Also, the composition of workforce is different. Matched domestic firms employ by six percentage points more women and are much less active in hiring than what is typical for the universe of domestic firms. Both matched treated and control firms employ a higher skilled workforce than the total population of treated and control firms, considering education as well as the skill content of jobs. Regarding differences in individual characteristics within the matched sample, the advantages of acquired firms observed in Table 2.3 remain; although the quality of the workforce of matched domestic firms approach more that of matched foreign firms than what we saw in the full sample.

To compare differences in mean wages in the full and the matched samples, we apply the decomposition method suggested by Ñopo (2008). The original idea of Ñopo addresses the potential common support problem in Oaxaca-Blinder (OB) type of decompositions.[54] Take the gender wage gap as an example. The OB decomposition builds on estimating actual earnings equations for both genders, and on estimating counterfactual equations, e.g. of the form: What would be the expected wage of men, if the distribution of their individual characteristics aligned perfectly to that of women? There is an inherent misspecification possibility in the OB method if the distributions of characteristics for men and women do not have common support.

Ñopo suggests applying matching techniques to divide the distributions of both genders into a part in the common support (i.e. those individuals who could be matched based on their individual characteristics) and a part out of the common support (i.e. those individuals who could not be matched). Then, he decomposes the total mean wage gap into four parts: the wage gap between men and women in the matched subsample, which is further decomposed by the regular OB decomposition into composition and unexplained effects; the difference in mean wages between matched and unmatched males; and the difference in mean wages between matched and unmatched females.

[54] For more on the Oaxaca-Blinder decomposition, please consult the seminal papers by Oaxaca (1973) and Blinder (1973).

We will only apply a simplified version of the Ñopo decomposition, and set aside the OB decomposition on the common support. We are interested in the question: What part of the total gap in mean wages between acquired and non-acquired firms is explained by differences in wages of similar foreign and domestic firms (i.e. in the matched sample), and what part is due to differences in wages between in-the-support and out-of-support acquired and always domestic firms, respectively?

More formally, let $E(w|t)$, $E_m(w|t)$ and $E_{nm}(w|t)$ denote the mean of log real wages in the full sample, in the matched sample and in the non-matched part of the full sample, respectively, where $t = T$ for treated (acquired) firms and $t = C$ for control (always domestic) firms. Let γ_t denote the share of observations in the full sample that could not be matched. Then we can express mean wages in the full sample as a weighted average of the mean in the matched part and of the mean in the unmatched part of the full sample. That is,

(5) $$E(w|t) = (1-\gamma_t)E_{nm}(w|t) + \gamma_t E_m(w|t) = \gamma_t[E_{nm}(w|t) - E_m(w|t)] + E_m(w|t), \qquad \text{for t = T,C.}$$

If we substitute (3) into the wage gap in the full sample, $E(w|T) - E(w|C)$, then we get the following decomposition:

(6) $$E(w|T) - E(w|C) = [E_m(w|T) - E_m(w|C)] + \\ + \gamma_T[E_{nm}(w|T) - E_m(w|T)] + \gamma_C[E_m(w|C) - E_{nm}(w|C)],$$

where the first term in the sum represents the difference in mean wages between acquired and non-acquired firms in the matched sample, the second term shows how non-matched treated firms differ from matched treated firms (weighted by the relative frequency of non-matched observations in the treated group), and the third term gives the wage gap between matched domestic and non-matched domestic companies (weighted by the relative frequency of non-matched observations in the control group).

To perform the decomposition we first remove year and region effects from log wages by running simple pooled OLS regressions and then we estimate (4) non-parametrically by computing weighted averages of the residuals. We do this for both of our firm-level data (where one unit of observation is the log of the average wage bill in a firm-year), and for the LEED (where one unit of observation is the log of monthly earnings in a worker-year). We present the results in Table 2.9.

The wage gap in the full sample is very large in both datasets: 583 log points in the firm-level sample and 442 log points in the LEED. The difference in mean wages in the matched sample is around eighty percent of the total gap in the firm data, and about seventy percent in the individual data.

Independently of the level of aggregation, matched control firms pay by approximately twenty percent higher wages than unmatched control firms, increasing the estimate in the full samples compared to that on the common support. Surprisingly, also matched treated firms are of higher wages than their non-matched peers which decreases the estimated total wage premium.

We now move on to a parametric analysis of the acquisition wage premium for the universe of firms and for a matched subsample of acquired and domestic firms that are similar along other dimensions than treatment status.

2.5. The Effect of FDI on Average Wages and on the Wage Structure

2.5.1. Estimation of the Average Effect

This section presents estimates of the average effect of FDI on wages using both the firm-level and worker-level data and applying a range of econometric approaches. We present estimates both for firms and workers because, as discussed in the introduction, the appropriate level of analysis is ambiguous, and in order to take advantage of the benefits of different types of data and examine the robustness of results. In terms of econometric methods, simple OLS regressions on the full samples function as benchmarks for our attempts to distinguish selection bias from causal effects, and they provide measures of average wage differentials for firms by all ownership types. Our attempts to handle selection, or endogeneity of ownership, fall into several categories, each of which has advantages and disadvantages. In most cases, the estimates are identified only for a subsample of the data, restricted for instance to firms that change ownership in certain ways, or to incumbent workers who remain in a firm after acquisition. Thus, the differences in point estimates we present may result from the changes in identifying variation across these subsamples as well as from the differences in econometric approach.

Table 2.10 contains basic OLS estimates for the firm and worker data, respectively, in which the FDI variable is a simple dummy based on majority foreign ownership. The results for the full firm-level data are weighted by the number of employees in the firm-year. They imply a 64 log point wage differential controlling only for region and year effects (to account for price differences). The estimate falls by 10 points when controls for 2-digit industries are added, thus implying some selection of higher wage industries by foreign investors. The simple average FDI effect estimated with the LEED data, shown in the first column of results, implies a 46 log point differential.[55]

The LEED of course permits us to include worker characteristics and we report 3 alternative specifications with different sets of control variables: (1) controls for gender, three educational dummies (vocational, high school, university, the omitted variable being elementary education), a quadratic function of potential experience and interactions between these variables which are demeaned to allow the non-interacted variables show the average effect, (2) additional controls for job characteristics (a dummy variable indicating that the worker was hired during the previous year and seven broad occupational categories), (3) additional controls for 2-digit industry. Job characteristics and industry may well be jointly determined with respect of foreign ownership and these results should be treated with caution. Nevertheless, they shed light on the robustness of the results, which indeed show remarkably little variation across the first two specifications; the inclusion of individual characteristics decreases the foreign effect by only 4-5 log points.[56] Including industrial controls further decreases the effect by 10 log points but it is still as large as 0.315. The estimated wage effects of worker characteristics are always highly statistically significant and are in the usual range. Depending on the controls used, the gender wage gap is 0.17 to 0.22. Compared to workers with elementary education, the wage premium associated with vocational studies is 0.05 to 0.10, high school 0.17 to 0.35, and university degree is 0.54 to 0.90. One year of potential experience increases the wage of the average worker by 1.8 to 2.4 percent and the profile is conventionally concave.[57]

Table 2.11 adds several types of fixed effects to the regressions on both the firm and worker data, in the latter case using the set of controls from specification (2) from Table 2.10 (and henceforth in the paper, except where they drop out because of collinearity with worker fixed effects). Compared to the OLS specification, the firm-level estimate with firm fixed effects (FFE) shown in the top panel of Table 2.11 falls by more than half, but the estimate of 27 log points is still large and statistically significant. The FFE result from the LEED in the lower panel of the table decreases by even more in proportional terms to 15.8 log points, again highly significant.[58] When we control for worker group

[55] The difference between firm-level and worker-level estimates is quite large, and the higher magnitude of the firm-level estimate contrasts with studies examining wage effects associated with trade union (see, e.g., Pencavel 1991) and privatization (Earle and Telegdy 2008). We will shortly discuss the reasons behind this difference later in the paper.

[56] We also run a specification when we control only for gender, education and potential experience, but not their interactions and the results are virtually identical to those presented in the table.

[57] We do not report these estimates in the table, but the average wage of employees with less than one year of job tenure is 8 to 12 percent less than average wages of workers with more than one year of job tenure, and the pattern of estimated coefficients on occupational dummies accords with expectations. These results are available from the authors on request.

[58] In this case, it appears that two factors generate the difference between firm- and worker-level results: the different wage variables (average versus individual wages) and the missing years in the LEED data. If we use firm-level average wages in

fixed effects within firm (GFE), the foreign wage premium declines only 3 log points, and the inclusion of firm-worker fixed effects (FWFE, defined for those workers who do not change employer from one year to another) decreases the foreign effect to 5.1 log points, still statistically significant. The latter result implies the wage gain for incumbent workers who remain with the firm for at least one year after the ownership change takes place.

The analysis so far treated all foreign firms equally and did not distinguish between single acquisitions from those when a foreign takeover is followed by a divestment. In the regressions with a single foreign dummy variable we made the implicit assumption that the foreign wage effect is symmetric in both directions, but an interesting question is whether this assumption is correct. These specifications allow us to examine differences between firms that were kept in foreign ownership and those which were further divested to domestic entrepreneurs. In addition, by looking at those firms which experienced both acquisitions and divestments during the period observed, we can estimate the symmetry of the foreign wage effect for both acquisitions and divestments within firms, eliminating any fixed differences between acquisitions and divestments.

Table 2.12 presents the FFE results based on the firm data for the whole sample and for a matched sample where we construct a common support for the control and treatment groups. In the full sample we estimate very similar acquisition effects for the two types of acquisitions (single ones and those followed by a divestment). The foreign wage effects based on these estimations increases wages by 28-30 log points. In the matched sample the effects decline only to a small extent but they differ from each other. Single acquisitions increase wages by 25, and those followed by a divestment by 21 log points.

The divestment effects indeed show a reversal of the foreign wage effect. In the full sample the coefficient measuring wages in the post-divestment period is 0.164 or smaller by 13.4 log points than the acquisition effect – wages do fall after divestment but they are still larger than in the pre-acquisition period. In the matched sample the reversal is almost complete as the divestment coefficient is only 0.076 and it is not significant at any conventional level. This analysis provides evidence, therefore, that a large part of the foreign wage effect indeed is associated with foreign ownership as it disappears when the foreign owners are not present in the company.[59]

In Table 2.13 we present the results for the LEED sample in 3 specifications (firm fixed effects FFE, firm-worker group fixed effects GFE and firm-worker fixed effects FWFE) for the full and the

both datasets and restrict the comprehensive firm data to only those firm-years in which firms are observed in the LEED data, we get very similar foreign wage premia.

[59] An alternative explanation for the small divestment effects may be selective mobility of foreign owners. If the firm is not doing well (which is reflected in low wages) it is more likely that the foreign owner sells the firm.

matched samples. To start with the full sample, the effects are similar for the two acquisition types but they are always larger by several log points in the case of those firms which were later divested. In the FFE the acquisition effect is 17-21 log points, which falls only little when firm-worker group effects are included. The firm-worker fixed effects estimation predicts that incumbent workers' wages increase by 5-8 log points after the takeover. The divestment effects are qualitatively similar to what we found in the firm data but the reversal is smaller. In the matched sample the acquisition effects are mostly similar, albeit smaller to the full sample results in the FFE and GFE specifications while we find a wage effect for incumbent workers only in the case of firms later divested. The divestment effects, however, are small and insignificant in all three specifications showing that wages after divestment are essentially the same as they were before the foreign acquisition.

How does the effect evolve in time? Are the new foreign owners raise wages shortly after the acquisition and do not change them later, or they rather increase them gradually? To test for the nature of the wage increase, we run the same regressions as before but we add a post-acquisition trend an overall trend as well to control for possible group effects in the progress of wages. As shown in Table 2.14, the coefficient on the overall trend is always positive and significant, but its inclusion to the estimation does eliminate the acquisition level effect which remains positive, sizable and significant. The post-acquisition trend, on the contrary, is zero in three out of four samples while in the full firm sample we measure a negative trend coefficient which suggests that the overall foreign effect would disappear in about 11 years. While this outlier of this demanding specification diminishes the robustness of our results to some extent, the results found in the matched samples – where the treated and untreated firms are similar – support our baseline results and in addition to it, show that the foreign wage effect is a one-time increase in wages which does not change.

2.5.2. Effect of FDI on the Wage Structure

Our analysis has established a robust and positive average treatment effect of foreign ownership on wages, but we have not studied the effect on various worker groups. Are there some worker types which win, and some others which lose wages as a result of foreign ownership, or everybody benefits and receives a positive foreign wage premium? Foreign ownership is usually associated with high quality products and services, better technology and better corporate culture so one could hypothesize that workers with high levels of human capital get higher wages relative to their less endowed colleagues. To test this, we interact foreign ownership with worker characteristics and run the same regressions as before. In the first set of regressions we test how the foreign wage effect varies with gender, education and experience. Table 2.15 shows that the wage effect of the reference group (incumbent male workers with elementary education and 10 to 20 years of experience) is large and significant in all four specifications. The estimated effects of the interaction terms provide evidence that relative wages indeed change after a foreign acquisition: some of them are negative while others larger than zero and their magnitude also varies. Nevertheless, they are never larger than the main effect, showing that foreign ownership increases the wages of both genders, all types of education, and experience groups, as well as new hires and workers with longer tenure. The results show that better education is associated with higher foreign wage effects and the wage premium declines with experience. The estimated wage differential across the two genders is small and statistically insignificant, as well as the differential between new hires and incumbent workers. The universal increase of wages is true for the occupational structure as well. In Table 2.16 we interact the foreign acquisition dummy with 2-digit occupational dummies: the estimated effects are all positive and almost always significant.

We also run quantile regressions to test how the effect varies along the wage distribution in the sample.[60] The results, shown in Figure 2.4, sustain the findings from Tables 2.15 and 2.16. Workers in the lowest decile in the wage distribution experience a wage increase of 32 log points in the full sample and 20 log points in the matched sample while those in the 9th decile have a wage effect larger by 10 log points. Therefore, while high paid workers indeed benefit more from foreign acquisitions than low paid workers, even the lowest wage category receives a significant foreign wage premium.

2.5.3. Robustness Checks

One possible objection to the analysis above concerns measurement error in the wage variable, which is correlated with ownership. First, working hours may be different under domestic and private ownership. As the wage variable used in this analysis is the yearly average in the firm data and monthly in the LEED, we do not capture any variation in working hours. The LEED, however, provide information on hours actually worked after 1999 and we use this to test for possible biases. We run similar regressions as before but with working hours as the dependent variable.[61] The estimated coefficients, shown in Table A2.4, are small and imprecisely estimated, showing that hours are probably not very different across ownership types.[62]

[60] Note that we cannot take into account selection on unobservables in the quantile regressions.

[61] A more natural test would be the replacement of monthly wage with hourly wage in our regressions, but the wage variable includes several types of payments which do not vary directly with hours worked.

[62] The measurement of working hours is probably very cumbersome in the case of white collar workers. As a robustness test, we rerun the regressions with only blue collar workers, and obtained similar results.

Second, wages can be biased due to underreporting to decrease tax payments. The tax burden on employment is high in Hungary and tax avoidance is widely considered rife. If underreporting is more prevalent in domestic firms, the estimated foreign effect may be upward biased. To check whether domestic firms are indeed more likely to avoid taxes than foreign-owned enterprises, we carry out two tests, shown in Tables A2.5a and A2.5b for the firm level sample and LEED, respectively. First, we interact the foreign dummy with a cheating index which is defined at the industry level and shows the likeliness of cheating (Elek et al., 2008). Our results show that in industries where underreporting is less likely, the foreign wage difference is larger than in cheating industries. Both of these set of results reject the hypothesis of domestic firms being less honest in terms of reporting true earnings, although they are also consistent with other differences across size and industry categories in how foreign firms operate. As a second test, we replace wages with a dependent variable indicating whether the worker was paid very close to the minimum wage that year (defined as being paid less than 3 percent more than the minimum wage). We find that a lower proportion of workers were paid the minimum wage in foreign-owned companies, and the estimated coefficient is significantly different from zero. This result may suggest more misreporting in domestic firms, but the magnitude of the coefficient is rather small (0.038 – 0.066). As only about 10 percent of workers receive the minimum wage in our sample, this wage differential cannot explain the 9 to 15 percentage points foreign wage premium.[63]

To summarize, all of the analyses imply a positive, statistically significant wage effect of foreign acquisitions. The matched samples provide the most credible evidence, especially together with the reversal of the FDI effect in cases where acquired firms are subsequently divested to domestic owners. The estimated FDI effect tends to be smaller in the LEED than in the firm-level data, but still higher than those estimated in other countries. In the next section we explore possible mechanisms which could account for the foreign wage premium.

2.6. Possible Explanations of the Foreign Wage Premium

The evidence presented in the previous section suggest that foreign ownership is associated with higher wages, even when we control for various forms of ownership selection, firm and worker heterogeneity and measurement error in wages. Why would foreign-owned firms pay higher wages? Several possible explanations exist, including changes in productivity and rent sharing, the measurement of job attributes, or untreated selection at the firm and worker level. In this section we

[63] This result can also be interpreted as another piece of evidence for the foreign wage premium.

discuss each of these issues and try to provide relevant empirical evidence. In what follows we present only the matched regressions controlling for firm fixed-effects.

2.6.1. The relation between productivity and wage effects

Is the FDI wage premium, which seems to persist in our data regardless of any attempt to repress it, associated with higher productivity?[64] To examine the wage-productivity relationship, we estimate a seemingly unrelated regression model at the firm level, where the dependent variables are labor productivity and average compensation. In a second specification we control for capital and material costs per worker, which essentially changes the regression into a Cobb-Douglas production function divided by the number of workers.[65] By comparing the magnitudes of the two estimated coefficients, we can draw conclusions about the similarity of the productivity and wage effects. Table 2.17 contains the results, which show a wage effect of 24.7 percent, similar to what we obtained before. The labor productivity effect of foreign ownership is 39.2 percent, much larger than the wage effect. The 14.5 percentage point difference in the two effects can be the result of the productivity effects of capital and the rents going to the owners of capital – the foreign investors. Indeed, when we control for capital and material costs per worker in both equations in column 3 of the table, we find very similar wage and productivity effects: the foreign coefficient of the wage equation drops to 16 percent, while the labor productivity effect falls much more to 19.5 percent. The difference in the two coefficients is 0.032 or 16 percent of the wage effect.[66]

Why then are the wage effects of FDI in Hungary so high? One possibility is that Hungarian firms started the transition in a backward condition, technologically and organizationally far from the frontier, and thus it was relatively easy for foreign investors to raise productivity and wages. To examine this, we do several tests. First, we collected data on the origin of the foreign owner by source country.[67] Our assumption is that on average, owners from more developed countries are likely to bring more up-to-date technology and organizational capital and so increase labor productivity.[68] We test this assumption by interacting the foreign ownership dummy with the proportional difference between the GDP *per capita* of the source country of FDI and the Hungarian figure.

[64] As we discussed in the introduction, if labor markets are competitive, high firm productivity is not sufficient to having higher wages but combined with different types of rent sharing (e.g., efficiency wages or union activity) can lead to it.

[65] In these specifications we replace the year controls with industry-year interactions, to measure productivity more precisely.

[66] The formal test rejects equality, but that is not unexpected with such a large sample. The correlation of the residuals from the two equations is quite high (ranging between 0.239 and 0.460), and again the Breusch-Pagan test rejects uncorrelatedness.

[67] As Table A2.6 shows, foreign investors come predominantly from continental European countries.

[68] An alternative assumption is that those owners who are used to paying high wages are more likely to raise wages of Hungarian workers for equity reasons or for motivating them to exert more effort or not leave the firm.

We also test whether the wage effect varies with the timing of the foreign acquisition. Domestic firms were further away from their production possibilities frontier at the beginning of transition and wages were also smaller than in latter periods. Therefore, in early transition foreign owners had more space for improvement than later. As an additional test, we disaggregate the target firms by their ownership type into state and privately owned firms and test whether the foreign acquisition effect is different across the two types. Here the hypothesis is that state-owned firms are further from their production possibilities frontier so foreign ownership may have larger effect on them.

Finally, we test how firm size alters foreign wage premium. Large firms are likely to be acquired by large multinational companies, while small firm takeovers are more probably cross border small investment. These types of owners are likely to behave differently. True multinationals are associated with up-to-date technology and know-how while cross border investment probably does not have these features. To test for this, we interact the foreign ownership dummy with firms with their average size below (above) 50 employees.

In the top panel of Table 2.18 we first show how the foreign wage effect varies by the grade of development of the sending country of FDI. The interaction term between the relative GDP *per capita* and the foreign acquisition dummy variable is positive and significant in both samples, showing that the foreign wage effect is higher for more wealthy sending countries. Early and late acquisitions have similar estimated wage effects in the firm sample, but they do differ in the LEED. While those acquisitions which took place before 1998 raise wages by 15 percent, those which happened after this year have an effect of only 9 percent. The next lower panel of the table permits the FDI acquisition effect to vary between state-owned targets (i.e., privatizations) and those that are domestic private. Again, the estimated FDI effect is larger for the former firms, which were inherited from the central planning system, and therefore are likely to be farther from the productivity (and wage) frontiers. The heterogeneity of the wage effect by the ownership of the target firms is quite large in the firm level sample, where foreign ownership raises the average wage of domestic firms by 10, and for state owned firms by more than 30 percent. This difference is estimated to be much smaller in the LEED, where the two effects are 10 and 14 percent.

The estimated wage effect differs by size as well. The foreign wage effect of small target firms is very close to zero, while it is large and significant for large firms in both samples (0.26 and 0.13 in the firm sample and LEED, respectively).[69]

[69] Another interpretation of this result is one of tax evasion: it is likely that underreporting is inversely proportional to the size of the company as it is harder to imagine that in a large corporation workers are paid under the table than in small firms, where managers and workers are working closely together and can trust that this practice will not be reported to the tax

2.6.2. Worker composition

Although the focus of the paper is the wage effect of foreign ownership, composition may clearly affect wages in the firm level sample: average wages can increase even in absence of a foreign effect if the foreign owner hires more educated workers, for example. In the LEED we control for worker characteristics and thus this problem is reduced to the unobservable characteristics of workers. To gauge how large the bias due to workforce change can be, we test how the composition of workers changed around the acquisition. We run linear probability models with firm fixed effects where the dependent variables are worker characteristics and the right hand size is the same as in Equation (1).[70] Including firm fixed effects implies that the estimated coefficients show how the workforce changes after the foreign takeover relative to pre-takeover within firm composition. We report the estimated coefficients of the foreign acquisition dummy in Table 2.19. The results show small changes in composition after the ownership change. Female and vocational workers' proportions fall by 2 percent and university graduates increase their presence in foreign owned firms by 4.5 percent. Potential experience falls by almost 1 year which may show the effect of more university graduates or a fall in the average age of the workforce. The proportion of newly hired workers does not change after the takeover. In conclusion, these results do not support the hypothesis that the composition of workers changed after the takeover to a large extent.

2.7. Conclusions

This paper investigated the effect of inward foreign acquisitions on earnings in Hungary. To identify the effect, we analyzed two datasets from which we selected firms that were ever acquired by foreign investors and always domestic firms. On the one hand, we work with an administrative panel of firms that virtually includes all double-entry book-keeping legal entities in the Hungarian corporate sector; and with a rich linked employer-employee dataset (LEED) that follows firms in time and in which about fifty percent of workers who stay with the same employer can be also linked longitudinally. The LEED only comprises a representative sample of the population of firms operating in the corporate sector, but contains valuable information on various worker characteristics. Thus, our identification strategy was mostly built on firms changing ownership status, but we could also identify

authority. If this is the case, the wage effect should decrease by the size of the company as both the foreign and domestic firms are more likely to report the actual wages of workers.

[70] We also ran Equation (1) with total employment as a dependent variable. In the full sample the foreign effect is 0.117 (significant) while in the matched sample the estimated coefficient is -0.015 (insignificant).

the wage effect of FDI for incumbent workers of acquired firms. Our datasets – especially the firm-level one – contains more ownership changes involving foreign ownership and longer time series both pre- and post-acquisition than most previous studies, so we believe the data are well suited for the purposes of this kind of research.

We found that foreign ownership is correlated with higher earnings in a pooled OLS specification, and the wage premium is close to sixty percent in the firm-level data, and forty percent in the LEED, even after controlling for various worker and job characteristics. However, foreign owners "cherry-pick" high-wage domestic firms, as shown by the reduction of the foreign wage premium when we apply difference-in-differences methods to control for unobserved time-invariant heterogeneity of firms and of within-firm worker groups. The important role of selection is also evident when we combine fixed effects estimation with propensity score matching. We also match on pre-acquisition wages, to take into account selection on unobserved heterogeneity as well as possible.

Nonetheless, even in the specifications controlling for selection bias, we still find a positive and strongly significant foreign wage effect of 8-15 percent in case of acquisition, which is larger than what most studies find for developed countries. Since we observe a group of acquired firms that are divested back to domestic owners later in their life-cycle, we estimate a divestment wage effect to support our story of a true foreign effect as opposed to an acquisition effect. We find that wages almost revert back completely to their pre-acquisition level after divestments, which strengthens our beliefs in that we identify a foreign acquisition effect and not simply an acquisition effect.

What explains this gap between average earnings in foreign and domestic enterprises? We analyze three groups of possible explanations: selection and composition change, measurement error and productivity advantage.

Selection does account for the majority of the difference in earnings, but cannot account for the total premium. Composition effects might explain the remaining gap, since we find that some groups of workers benefit more than others: university graduates have an additional premium of eleven percent on top of the average foreign impact. Our results are however not indicative of a serious change in the observable composition of the workforce after the acquisition, although foreign owners do seem to hire more in favor of the very young (workers with 0-5 years of experience). We measure a five percent wage premium for workers that stay with the same employer during the foreign acquisition, and this rules out the possibility that it is only composition change that is driving our results.

We do not find any evidence that it is either higher working hours or underreported wages that explain the earnings differential. Although our methods here are not without caveats, we reject the hypotheses that employees of foreign-owned firms have to work longer and also that domestic employers are more inclined to underreport true earnings.

Our main candidate for explaining the wage differential between the two types of firms is the difference in the productivity of the workforce. Unfortunately, we cannot test this hypothesis directly, since we think that the major part of this difference is unobserved in the data, and we cannot follow workers that switch from a domestic to a foreign employer. Still, the productivity explanation is supported by a firm-level seemingly unrelated regression framework where we find similar foreign effects in the earnings and productivity equations and also the residuals from the two equations are strongly correlated. The heterogeneity of the acquisition effect is also in line with our productivity hypothesis. The wage effect is increasing in the GDP per capita of the foreign owner's country of origin. Also, since the wage effect is larger in early transition acquisitions and for state-owned acquisition targets, the productivity difference hypothesis supports a "catch-up" type of explanation, namely, that the wage effect of foreign acquisitions is higher when the target firm is probably farther away from its technological frontier.

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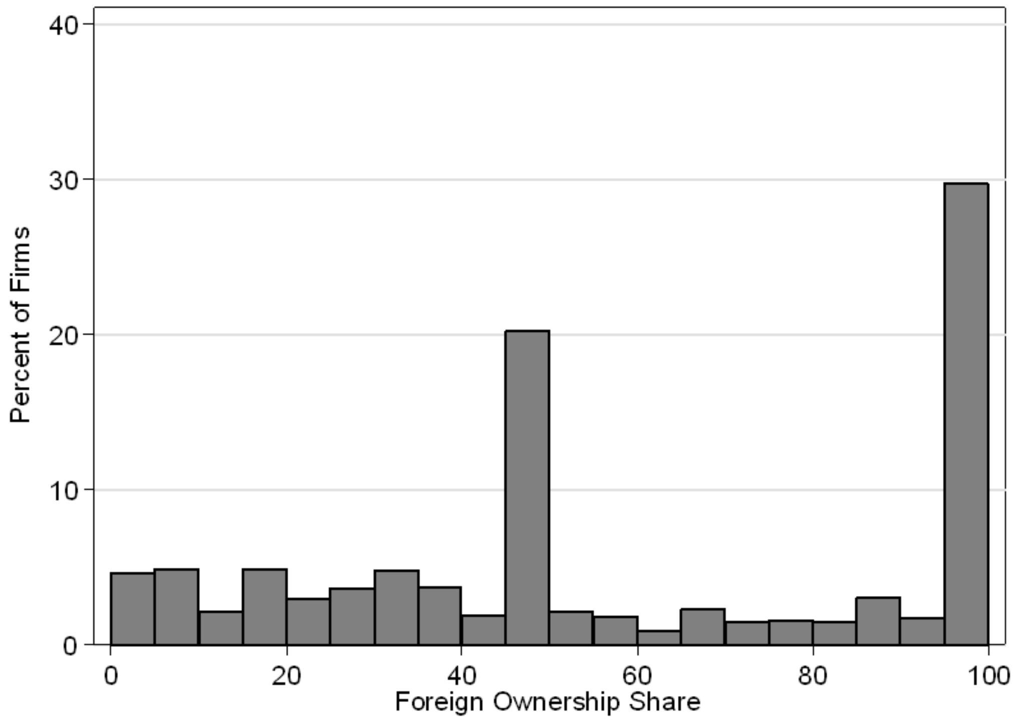
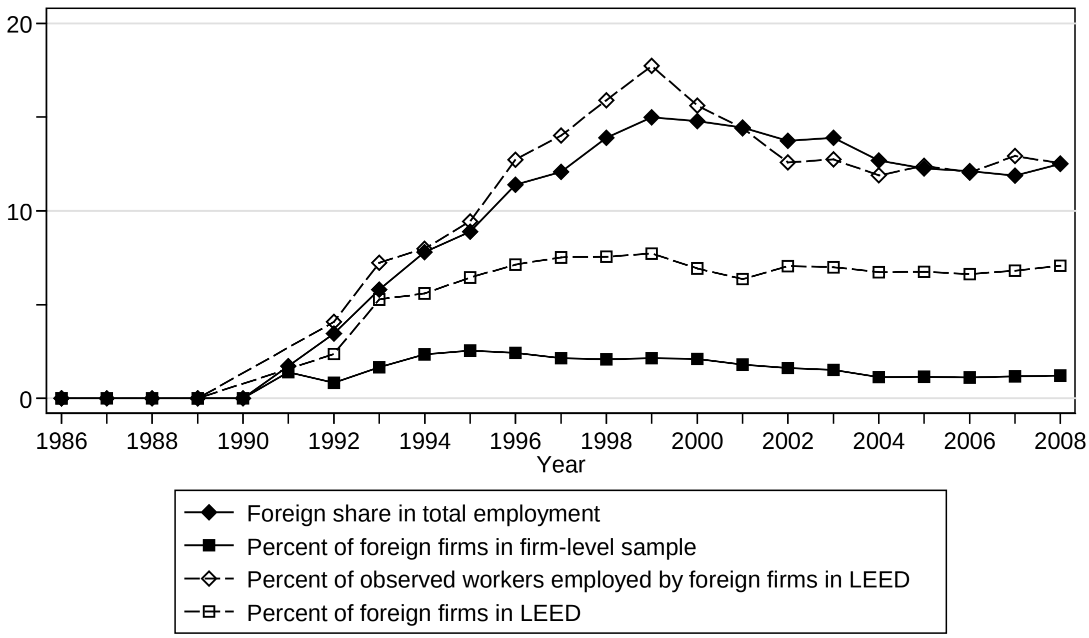
2.9. Tables and Figures

Figure 2.1: Distribution of Foreign Ownership Share in 2000



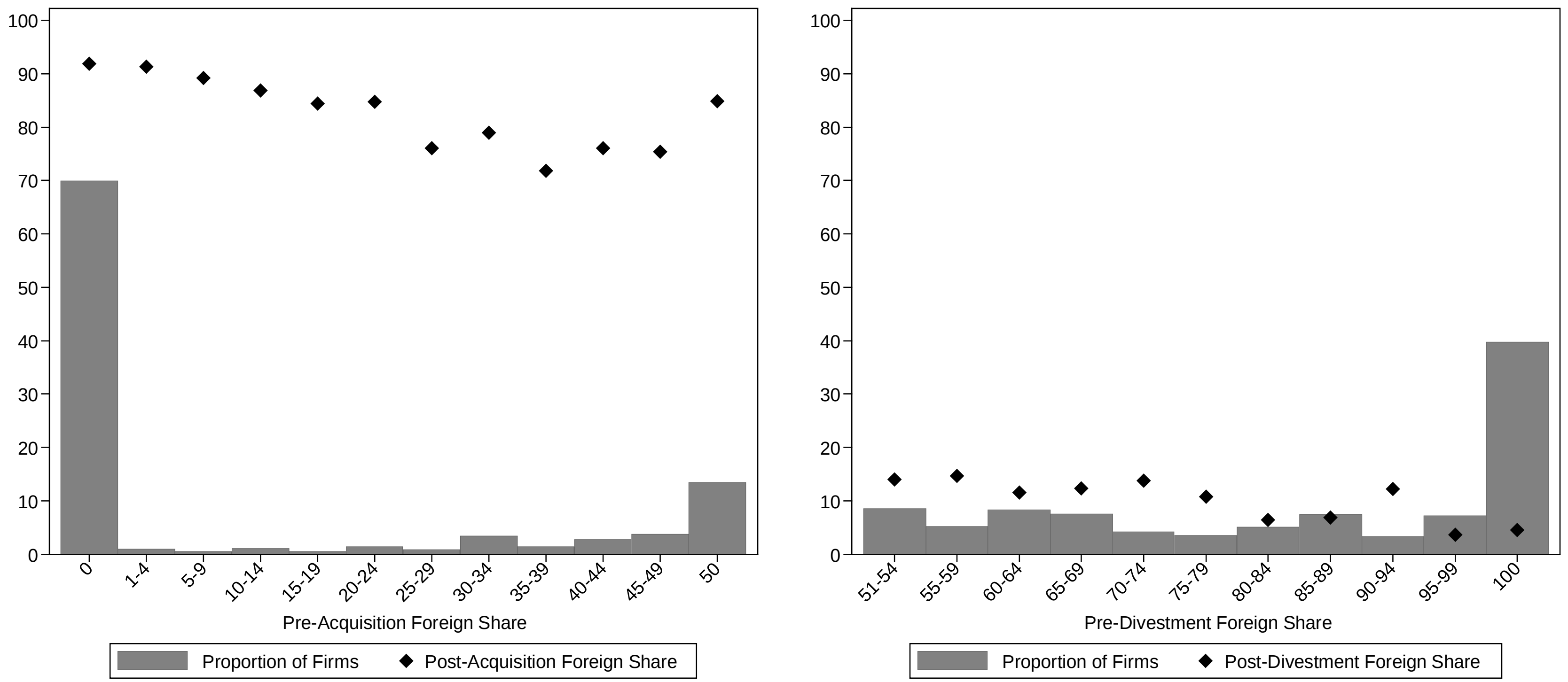
Notes: Foreign ownership share measured as the percentage of total equity held by foreign investors. Only firms with positive foreign ownership share included.

Figure 2.2: Evolution of Foreign Acquisitions



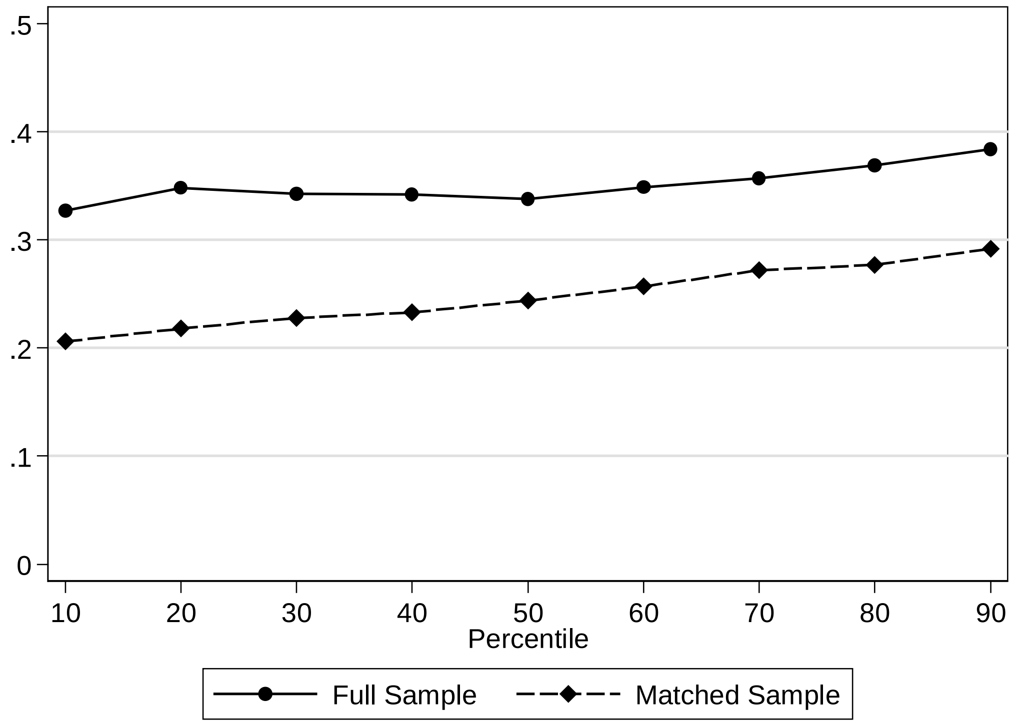
Notes: Percent foreign firms = percent of firms majority foreign owned. Foreign share in total employment = percentage of employees employed by foreign owned firms, calculated from the firm-level sample using sample weights. Foreign ownership means: More than 50% of total equity is owned by foreign owners.

Figure 2.3: Distribution of Foreign Ownership Before and After Foreign Acquisitions and Divestments



Notes: Bars depict the distribution of acquired (left panel) and of later divested (right panel) firms according to size of foreign ownership share in the last domestic year (for acquisitions), or in the last foreign year (for divestments) before the change in majority ownership. Diamonds show averages of foreign shares in the first foreign year (for acquisitions), or in the first domestic year (for divestments) after the change in majority ownership..

Figure 2.4: The Effect of Foreign Ownership on Wages by Quantiles



Notes: N = 2,487,055 for the full and 385,451 for the matching sample. Regression coefficients on foreign acquisition from quantile regressions that control for region, year and industry effects, and for post-divestment domestic period of acquired firms that are resold to domestic owners.

Table 2.1: Number of Observations on Ownership Switches with Pre- and Post-Treatment Wage Information – Full Samples

	Firm-Level Data	LEED
Number of Acquisitions	4,928	647
of which:		
Single Acquisitions	3,945	560
Domestic-Foreign-Domestic	983	87
Number of Acquisitions by Year		
1990	125	0
1991	87	20
1992	218	65
1993	415	64
1994	296	56
1995	264	58
1996	234	38
1997	300	53
1998	329	43
1999	302	37
2000	258	34
2001	242	24
2002	228	21
2003	212	20
2004	272	16
2005	294	22
2006	374	30
2007	478	46

Notes: For total number of switches, see Table A2a and A2b. Definition of Foreign ownership: More than 50% of the equity is owned by a foreign owner.

Table 2.2: Firm Characteristics in the Full Samples

	Firm-Level Sample			LEED		
	ALDO	DOFO	DOFODO	ALDO	DOFO	DOFODO
Average Annual Wage Bill per Worker	1,083.6	2,207.4	1,697.4	1,302.0	2,887.0	2,095.7
	(1,829.4)	(2,545.2)	(2,795.5)	(1,378.8)	(4,775.6)	(1230.6)
Tangible Assets	142.1	2,659.9	813.1	247.1	6,598.4	1,923.1
	(4,803.9)	(36,011.8)	(6,347.8)	(6,225.2)	(55,221.3)	(9,875.1)
Employment	22.4	137.9	76.6	38.6	310.8	167.2
	(366.3)	(686.1)	(559.8)	(441.6)	(1026.1)	(758.0)
Labor Productivity	23.0	74.9	34.1	27.1	474.5	36.0
	(171.4)	(1,110.4)	(99.7)	(526.6)	(6,251.0)	(51.8)
N	1,835,371	33,282	14,690	116,608	5,043	2,164
Industry in 2000						
Agriculture, Hunting, Fishing, Forestry	5.0	2.9	2.6	10.2	4.4	2.9
Mining, Electricity, Gas, Water Supply	0.6	1.3	0.9	1.7	2.3	1.7
Manufacturing	17.3	28.1	22.3	27.9	46.0	45.5
Construction	10.2	2.7	4.9	12.4	2.4	3.5
Wholesale, Retail Trade, Repair	31.2	35.2	38.0	23.8	19.3	20.5
Finance, Insurance, Real Estate	5.2	7.1	6.8	4.2	6.1	12.0
Business Services	19.4	11.6	12.9	10.2	8.8	4.6
Other Services	11.2	11.2	11.6	9.6	10.7	9.3
N	90,171	2,067	988	8,318	349	160

Notes: Pooled, weighted averages of firm-year observations. Average earnings measured in thousands, tangible assets and labor productivity in millions of 2008 HUF. Standard deviations in parentheses. Industrial distribution measured as percentages within ownership type. Definition of industries follows NACE Rev. 1.1. Business Services include Renting of machinery and equipment; Computer and related activities; Research and development and Other business activities. Other Services cover Hotels and restaurants; Transport, storage and communication; and Other community, social and personal service activities. ALDO: always domestic, always state-owned or domestic privatization. DOFO: Single acquisition. DOFODO: Domestic-Foreign-Domestic.

Table 2.3: Individual Characteristics by Ownership Type – LEED

	Domestic	**Foreign**
Monthly Earnings	137.3	237.2
	(120.9)	(247.6)
Female	38.1	42.4
Education		
Elementary	27.1	16.9
Vocational	33.9	28.7
High school	30.2	36.0
University	8.8	18.4
Experience	22.7	21.6
	(11.0)	(10.8)
New Hire	11.2	10.2
Occupation		
Elementary Occupations	10.1	5.0
Skilled Manual Workers	46.8	46.0
Service Workers	10.3	6.9
Clerks	7.5	6.2
Associate Professionals	12.7	18.2
Professionals	4.1	8.7
Managers	8.6	9.0
N	2,344,622	142,433

Notes: Weighted unconditional means and standard deviations. Earnings measured in thousands of 2008 HUF, deflated by CPI. Female, education, new hire and occupation measured as percentages of total workforce by ownership type. Standard deviations in parentheses. The definition of occupations follows ISCO-88 where Elementary Occupations, Service Workers, Clerks, Associate Professionals, Professionals and Managers coincide with the corresponding major groups; while Skilled Manual Workers cover Skilled agricultural and fishery workers, Craft and related trades workers and Plant and machine operators and assemblers.

Table 2.4: Balance of Covariates in the Matched Sample, One Year Before Acquisition

	Normalized Difference Treated - Controls	
	Firm-Level Sample	LEED
Average Earnings	0.003	0.024
Employment	0.019	0.006
Wage Growth	0.025	-0.019
Employment Growth	0.003	0.023
Capital Intensity	0.013	0.005
Labor Productivity	0.007	0.014

Notes: Difference in averages by treatment status, scaled by the square root of the sum of variances. Mean of control observations subtracted from mean of treated observations. Differences computed one year before ownership change.

Table 2.5: Number of Observations on Ownership Switches with Pre- and Post-Treatment Wage Information – Matched Samples

	Firm-Level Data	LEED
Number of Acquisitions	1,756	476
of which:		
Single Acquisitions	1,355	414
Domestic-Foreign-Domestic	401	62
Number of Acquisitions by Year		
1990	6	0
1991	10	16
1992	95	36
1993	69	37
1994	128	39
1995	123	42
1996	106	33
1997	129	45
1998	124	42
1999	123	29
2000	129	28
2001	107	23
2002	105	20
2003	96	19
2004	109	13
2005	104	18
2006	189	27
2007	4	9

Notes: Definition of Foreign ownership: More than 50% of the equity is owned by a foreign owner.

Table 2.6: Comparison of Matched and Full Samples

	Firm-Level Sample		LEED	
	Full	**Matched**	**Full**	**Matched**
Average Annual Wage Bill per Worker	1,109.5	2,018.2	1,327.8	2,237.1
	(1,862.1)	(2,780.2)	(1,484.4)	(1,786.1)
Tangible Assets	196.3	2529.3	339.2	4,578.9
	(6,918.6)	(31,277.7)	(8,822.6)	(41,109.4)
Employment	25.0	194.2	42.7	306.4
	(377.0)	(1,371.6)	(457.8)	(1558.0)
Labor Productivity	24.0	62.9	32.9	55.0
	(227.2)	(950.5)	(882.2)	(185.1)
N	1,883,343	44,406	123,815	9,024
Industry in 2000				
Agriculture, Hunting, Fishing, Forestry	4.7	3.9	10.0	4.0
Mining, Electricity, Gas, Water Supply	0.6	1.5	1.7	2.4
Manufacturing	17.7	28.4	28.5	46.8
Construction	10.0	3.7	12.1	2.4
Wholesale, Retail Trade, Repair	31.3	32.4	23.7	17.8
Finance, Insurance, Real Estate	5.3	6.2	4.3	6.3
Business Services	19.1	12.6	10.1	9.5
Other Services	11.2	11.3	9.6	10.8
N	92,605	2,738	8,827	628

Notes: Pooled, weighted averages of firm-year observations. Average earnings measured in thousands, tangible assets and labor productivity in millions of 2008 HUF. Standard deviations in parentheses. Industrial distribution measured as percentages within ownership type. Definition of industries follows NACE Rev. 1.1. Business Services include Renting of machinery and equipment; Computer and related activities; Research and development and Other business activities. Other Services cover Hotels and restaurants; Transport, storage and communication; and Other community, social and personal service activities.

Table 2.7: Firm Characteristics in Matched Samples

	Firm-Level Sample			LEED		
	ALDO	DOFO	DOFODO	ALDO	DOFO	DOFODO
Average Annual Wage Bill per Worker	1,923.2	2,262.0	1,739.6	2,068.6	2,495.9	2,101.6
	(3,159.7)	(2,505.6)	(1,581.0)	(1,923.5)	(1,674.3)	(1,351.9)
Tangible Assets	1,444.9	4,535.4	1,385.6	1,802.2	8,530.4	3,464.5
	(10,095.3)	(50,832.3)	(8,937.0)	(9,973.9)	(64,558.0)	(14,515.4)
Employment	204.7	216.6	93.6	268.9	384.0	205.7
	(1,747.9)	(905.3)	(321.2)	(1,913.8)	(1,198.2)	(453.9)
Labor Productivity	45.4	98.7	36.3	60.1	56.9	35.3
	(372.4)	(1,538.0)	(71.3)	(181.1)	(214.5)	(31.2)
N	23,130	15,489	5,787	4,129	3,943	952
Industry in 2000						
Agriculture, Hunting, Fishing, Forestry	4.2	4.2	2.6	3.5	5.6	3.6
Mining, Electricity, Gas, Water Supply	1.2	1.9	1.3	2.1	2.5	0.0
Manufacturing	27.0	32.2	23.3	48.0	46.5	42.4
Construction	4.1	2.9	4.4	1.6	2.3	6.1
Wholesale, Retail Trade, Repair	33.6	29.4	36.2	14.0	22.5	16.4
Finance, Insurance, Real Estate	6.0	6.2	7.2	3.5	7.1	16.1
Business Services	13.0	11.7	13.7	13.3	5.4	8.9
Other Services	11.0	11.5	11.4	13.9	8.3	6.6
N	1,354	994	390	283	276	69

Notes: Pooled, weighted averages of firm-year observations. Average earnings measured in thousands, tangible assets and labor productivity in millions of 2008 HUF. Standard deviations in parentheses. Industrial distribution measured as percentages within ownership type. Definition of industries follows NACE Rev. 1.1. Business Services include Renting of machinery and equipment; Computer and related activities; Research and development and Other business activities. Other Services cover Hotels and restaurants; Transport, storage and communication; and Other community, social and personal service activities. ALDO: always domestic, always state-owned or domestic privatization. DOFO: Single acquisition. DOFODO: Domestic-Foreign-Domestic.

Table 2.8: Individual Characteristics by Ownership Type – Matched LEED

	Domestic	Foreign
Monthly Earnings	165.5	251.8
	(143.5)	(258.1)
Female	44.3	42.4
Education		
Elementary	24.5	14.8
Vocational	27.3	26.6
High school	38.0	38.6
University	10.2	20.0
Experience	22.2	21.7
	(10.8)	(10.7)
New Hire	8.6	9.7
Occupation		
Elementary Occupations	8.0	4.1
Skilled Manual Workers	42.4	42.5
Service Workers	9.9	7.3
Clerks	6.7	6.6
Associate Professionals	20.8	20.5
Professionals	4.8	9.7
Managers	7.3	9.3
N	284,980	110,471

Notes: Weighted unconditional means and standard deviations. Earnings measured in thousands of 2008 HUF, deflated by CPI. Female, education, new hire and occupation measured as percentages of total workforce by ownership type. Standard deviations in parentheses. The definition of occupations follows ISCO-88 where Elementary Occupations, Service Workers, Clerks, Associate Professionals, Professionals and Managers coincide with the corresponding major groups; while Skilled Manual Workers cover Skilled agricultural and fishery workers, Craft and related trades workers and Plant and machine operators and assemblers.

Table 2.9: Ñopo Decomposition of Wage Differences between Acquired and Domestic Firms

	Firm-Level Sample	LEED
Total Difference	0.583	0.442
Difference in Matched Sample	0.485	0.309
Difference between:		
Non-Matched and Matched Treated	-0.111	-0.055
Matched and Non-Matched Control	0.210	0.189
N	1,884,875	2,487,069

Notes: Results of a non-parametric decomposition of the acquired-domestic wage gap in the full sample, following Ñopo (2008). Differences between weighted averages of residuals from pooled OLS regressions of log wages on region and year effects. Difference between non-matched and matched treated firms weighted by the share of non-matched treated firms in the universe of treated firms. Difference between matched and non-matched control firms weighted by the share of non-matched control firms in the universe of control firms. All results weighted by sample weights.

Table 2.10: The Effect of Foreign Ownership on Wages - OLS Estimation

	(1)	(2)	(3)	(4)
Firm-Level Sample				
Foreign	0.636**	N.A.	N.A.	0.534**
	(0.041)			(0.025)
R^2	0.162			0.307
LEED Sample				
Foreign	0.463**	0.420**	0.410**	0.315**
	(0.038)	(0.025)	(0.025)	(0.020)
Female		-0.215**	-0.196**	-0.174**
		(0.007)	(0.007)	(0.004)
Vocational		0.098**	0.051**	0.060**
		(0.005)	(0.005)	(0.004)
High school		0.350**	0.202**	0.171**
		(0.007)	(0.007)	(0.005)
University		0.897**	0.584**	0.539**
		(0.014)	(0.014)	(0.009)
Experience		0.024**	0.019**	0.018**
		(0.001)	(0.001)	(0.001)
$Experience^2 * 100$		-0.034**	-0.027**	-0.024**
		(0.001)	(0.001)	(0.001)
Gender, education, experience interactions	No	Yes	Yes	Yes
Job characteristics	No	No	Yes	Yes
Industry effects	No	No	No	Yes
R^2	0.125	0.359	0.406	0.464

Notes: N = 2,487,055 for LEED and 1,883,813 for firm-level sample. Dependent variable = ln(real gross earnings). *Foreign* = 1 if the firm is majority foreign owned in *t-1*. All equations include year and region effects. Job characteristics include dummy variables for workers hired in the previous calendar year, and for seven broad occupational groups. In specification (4) we control for two-digit NACE industry. Standard errors (corrected for firm clustering) are shown in parentheses. ** = significant at 0.01; * = significant at 0.05.

Table 2.11: The Effect of Foreign Acquisition on Wages – Estimations with Correction for Selection Bias, Firm-Level Data and LEED

	FFE	GFE	FWFE
Firm-Level Data			
Foreign	0.270**	N.A.	N.A.
	(0.024)		
R^2	0.250		
LEED			
Foreign	0.158**	0.128**	0.051**
	(0.016)	(0.018)	(0.012)
R^2	0.339	0.104	0.088

Notes: Firm-Level Data: We add firm fixed effects to the specification in column (1) of Table 2.10. Within R^2 reported. LEED: We add fixed effects at various levels to the specification in column (2) of Table 2.10. Firm fixed effects (FFE) control for unobserved employer-level heterogeneity. Group effects (GFE) control for unobserved heterogeneity by grouping employees within the same employer along the lines of gender, education, experience and county. Firm-worker effects (FWFE) control for unobserved individual heterogeneity for workers that can be followed over time within firm. In the LEED, under the GFE and FWFE regimes we omit individual characteristics and their interactions. Within R^2 reported for firm, group and firm-worker effects. N.A. means Non Applicable.

Table 2.12: The Effect of Foreign Acquisition by Type of Investment – Firm-Level Data

	Full Sample	Matched Sample
Single Acquisitions		
Acquisition Effect	0.283**	0.254**
	(0.031)	(0.031)
Domestic-Foreign-Domestic		
Acquisition Effect	0.298**	0.207**
	(0.046)	(0.056)
Divestment Effect	0.164**	0.076
	(0.063)	(0.058)
R^2	0.251	0.403

Notes: Firm fixed effects included. See the notes concerning firm-level data under Table 2.11. N = 1,883,331 for full sample and N = 44,406 for matching. Foreign acquisition: the firm was either majority state or majority domestic private in *t-2* and majority foreign in *t-1*. Divestment: the firm was majority foreign in *t-2* and majority domestic private in *t-1*. Within R^2 reported.

Table 2.13: The Effect of Foreign Ownership by Type of Investment – LEED

	FFE	GFE	FWFE
Full Sample			
Single Acquisitions			
Acquisition Effect	0.169**	0.128**	0.052**
	(0.020)	(0.024)	(0.016)
Domestic-Foreign-Domestic			
Acquisition Effect	0.212**	0.188**	0.083**
	(0.037)	(0.026)	(0.021)
Divestment Effect	0.142**	0.108**	0.051*
	(0.048)	(0.031)	(0.026)
R^2	0.340	0.104	0.088
Matched Sample			
Single Acquisitions			
Acquisition Effect	0.132**	0.130**	0.033
	(0.026)	(0.034)	(0.018)
Domestic-Foreign-Domestic			
Acquisition Effect	0.108**	0.147**	0.058*
	(0.026)	(0.030)	(0.023)
Divestment Effect	0.019	0.088	0.028
	(0.044)	(0.056)	(0.031)
R^2	0.433	0.112	0.124

Notes: See the notes concerning LEED under Table 2.11. N = 2,487,055 for full sample and N = 395,451 for LEED. Foreign acquisition: the firm was either majority state or majority domestic private in *t-2* and majority foreign in *t-1*. Divestment: the firm was majority foreign in *t-2* and majority domestic private in *t-1*. In the OLS specification, group effects control for time-invariant characteristics of firms with different ownership histories. Within R^2 reported.

Table 2.14: Difference-in-Differences Estimation of Levels and Trends of the Foreign Acquisition Effect

	Full Sample	Matched Sample
	FFE	FFE
Firm-Level Sample		
Foreign Overall Trend	0.022**	0.023*
	(0.008)	(0.010)
Acquisition Level Effect	0.193**	0.103**
	(0.022)	(0.030)
Acquisition Trend Effect	-0.018*	-0.001
	(0.008)	(0.010)
R^2	0.255	0.420
LEED		
Foreign Overall Trend	0.013**	0.010*
	(0.003)	(0.004)
Acquisition Level Effect	0.087**	0.061*
	(0.021)	(0.028)
Acquisition Trend Effect	-0.001	0.007
	(0.004)	(0.005)
R^2	0.340	0.440

Notes: Overall Trend: Coefficient on a trend variable interacted with the acquisition dummy. Level Effect: Coefficient on the acquisition dummy. Acquisition Trend Effect: Coefficient on the interaction of the acquisition dummy and a trend variable that is zero up to one year after the acquisition and starts increasing afterwards. Firm fixed effects included. Within R^2 reported.

Table 2.15: Effects of Foreign Acquisition on the Wage Structure by Gender, Education and Experience Groups

	FFE	GFE	Matching with FFE	Matching with GFE
Acquisition Effect of Reference Group	0.127**	0.138**	0.114**	0.107**
	(0.021)	(0.032)	(0.035)	(0.037)
Female	-0.011	0.035	-0.016	0.027
	(0.011)	(0.021)	(0.020)	(0.022)
Vocational	0.021*	-0.000	0.017	0.017
	(0.010)	(0.018)	(0.014)	(0.019)
High school	0.046**	0.009	0.047**	0.046*
	(0.013)	(0.030)	(0.015)	(0.021)
University	0.238**	0.086	0.119**	0.143**
	(0.032)	(0.054)	(0.038)	(0.033)
Experience: 0-10	-0.032**	-0.010	-0.017	-0.015
	(0.009)	(0.014)	(0.012)	(0.017)
Experience: 21-30	-0.015*	-0.039**	-0.038**	-0.046**
	(0.007)	(0.011)	(0.011)	(0.013)
Experience: 30+	-0.009	-0.061**	-0.044**	-0.068**
	(0.010)	(0.021)	(0.017)	(0.026)
New Hire	-0.033*	0.002	-0.008	0.014
	(0.015)	(0.011)	(0.022)	(0.023)
R^2	0.333	0.110	0.423	0.120

Notes: The table shows the estimated acquisition effect for a reference group, and estimated foreign wage returns to individual characteristics. Reference group: Males with elementary education and 11-20 years of potential labor market experience, who are not new hires. Coefficients and standard errors from a regression where the acquisition dummy is interacted with individual characteristics. Other control variables include year and region effects in GFE specifications, and in addition, main effects of the listed individual characteristics in FE specifications.

Table 2.16: Effects of Foreign Acquisition on the Wage Structure by Occupation

	FE	GFE	Matching with FE	Matching with GFE
Manager	0.474**	0.313**	0.217**	0.192**
	(0.043)	(0.057)	(0.046)	(0.049)
Professional	0.356**	0.218**	0.276**	0.248**
	(0.043)	(0.042)	(0.046)	(0.039)
Associate Professional	0.162**	0.131**	0.167**	0.159**
	(0.022)	(0.025)	(0.044)	(0.039)
Skilled non-manual	0.127**	0.083**	0.111**	0.090**
	(0.021)	(0.019)	(0.023)	(0.026)
Service	0.090	0.069	0.117	0.134*
	(0.058)	(0.060)	(0.062)	(0.066)
Skilled manual	0.121**	0.118**	0.089**	0.096**
	(0.019)	(0.020)	(0.021)	(0.030)
Unskilled	0.126**	0.160**	0.104**	0.123**
	(0.022)	(0.029)	(0.026)	(0.034)
R^2	0.327	0.200	0.432	0.240

Notes: The table shows the estimated acquisition effects for the listed occupational groups. Coefficients and standard errors from a regression where the acquisition dummy is interacted with occupational group dummies. Other control variables include year and region effects.

Table 2.17: The Effect of Acquisitions on Labor Productivity and Average Wages—Joint SUR Estimation, Matched Firm-Level Sample

	(1)	(2)	(3)
Average Compensation	0.247**	0.247**	0.163**
	(0.004)	(0.005)	(0.004)
Labor Productivity	0.392**	0.225**	0.195**
	(0.009)	(0.007)	(0.007)
Controls for Capital Intensity and Material Cost/Worker	No	Only in Productivity Equation	Yes
P-value ($\beta_{lp} = \beta_{comp}$)	0.000	0.004	0.000
Corr (u_{comp}, u_{lp})	0.460	0.239	0.269
Breusch-Pagan test	0.000	0.000	0.000

Note: Results from joint SUR estimation of a labor productivity, and an average earnings equation. Regressors in all specifications include: acquisition dummy, third-period domestic dummy for firms with domestic-foreign-domestic histories, industry-year interactions, and firm fixed-effects. Regressions are weighted by employment.

Table 2.18: FDI Impact Estimates by Acquisition Period, Type of Acquisition Target, Firm Size and Development of the Source Country – Matched Samples

	Firm-Level Sample	LEED
GDP per capita	0.033**	0.021**
	(0.007)	(0.004)
R^2	0.401	0.433
Early Acquisition	0.247**	0.149**
	(0.037)	(0.028)
Late Acquisition	0.251**	0.088**
	(0.091)	(0.027)
R^2	0.403	0.433
State-Owned	0.309**	0.141**
	(0.033)	(0.029)
Domestic Private	0.104**	0.102**
	(0.027)	(0.030)
R^2	0.411	0.433
Big	0.261**	0.133**
	(0.029)	(0.024)
Small	-0.009	0.001
	(0.029)	(0.040)
R^2	0.406	0.433

Notes: In the first panel, N = 26,823 for firm-level sample and 309,900 for LEED; in the next two panels, N = 44,406 for firm-level sample and 395,451 for LEED; while in the last panel, N = 44,344 for firm-level sample and 395,053 for LEED. All specifications include year and region dummies, and firm fixed effects; in addition, we control for gender, education, experience and their full interactions in the LEED. GDP per capita measures the difference between the source countries' and the Hungarian GDP per capita, relative to Hungarian GDP per capita. All GDP values measured in 2000 US dollars. GDP data is from World Bank. For a list and distribution of source countries, see Table A2.6. We consider acquisitions that took place in 1998 or before as early, while others as late transactions. Big firms have more than 50 employees on average over the sample period.

Table 2.19: Effects of Acquisitions on Observable Worker Composition

Dependent Variable	**Within-Firm Acquisition Effect**
Female	-0.021**
	(0.006)
Elementary	-0.004
	(0.011)
Vocational	-0.018*
	(0.008)
High school	-0.023
	(0.015)
University	0.045**
	(0.010)
Experience	-0.975**
	(0.298)
New hire	0.008
	(0.013)
N	395,451

Notes: Estimated coefficients on the foreign acquisition dummy from separate linear, worker-level probability regressions with listed individual characteristics as dependent variables; except for experience entered in levels. Regressions include firm fixed effects, year and region effects.

2.10. Appendix

Table A2.1a: Sample Size by Year - Firm-Level Data

	Unweighted	Weighted
Year	**Firm Observations**	**Total Employment**
1986	4,650	3,202,075
1987	4,959	3,137,100
1988	4,857	2,992,603
1989	3,989	3,399,483
1990	8,034	3,372,675
1991	9,719	3,566,973
1992	30,639	1,940,348
1993	37,344	1,729,086
1994	45,572	1,705,128
1995	50,520	1,643,654
1996	57,702	1,602,697
1997	72,041	1,632,054
1998	81,268	1,676,335
1999	86,752	1,662,683
2000	93,226	1,669,219
2001	108,943	1,684,207
2002	120,715	1,680,126
2003	131,403	1,680,525
2004	174,817	1,781,692
2005	180,312	1,770,864
2006	188,510	1,795,998
2007	192,702	1,766,865
2008	194,669	1,739,761
Total	1,883,343	N.A.

Note: Firm observations = number of firms with information on ownership and wages. Total employment = total employment in thousands, as represented by the weighted sum of workers employed by firms in the sample (approximating total employment in the corporate sector).

Table A2.1b: Sample Size by Year - LEED

	Unweighted		Weighted
Year	**Worker Observations**	**Firm Observations**	**Total Employment**
1986	523,715	3,673	3,491,514
1989	357,064	4,055	3,524,415
1992	76,804	5,023	1,916,722
1993	73,428	5,347	1,501,370
1994	93,252	7,151	1,618,363
1995	93,344	7,166	1,526,438
1996	89,113	6,688	1,483,755
1997	86,987	6,595	1,452,660
1998	86,648	6,512	1,464,256
1999	87,138	6,962	1,435,757
2000	98,849	8,827	1,564,394
2001	99,139	9,430	1,544,860
2002	102,970	6,732	1,613,371
2003	98,750	6,319	1,619,144
2004	107,756	7,005	1,694,641
2005	112,552	7,085	1,607,156
2006	103,207	6,636	1,719,621
2007	100,270	6,285	1,586,080
2008	96,060	6,324	1,648,292
Total	2,487,055	123,815	N.A.

Note: Workers observed = thousands of workers in the sample with information on earnings, education, experience, and gender. Firms observed = number of firms with information on ownership and location, and with at least one worker in the given year with information on earnings, education, experience, and gender. Total employment = total employment in thousands, as represented by the sum of weights in the sample (approximating total employment in the corporate sector).

Table A2.2a: Number of Firm-Year Observations by Type of Ownership Change – Firm-Level Data

	Total		Average	
Always Domestic	1,835,371		4.95	
	Total Before	Total After	Average Before	Average After
Single Acquisitions	14,091	19,191	3.74	5.09
Domestic-Foreign-Domestic				
Acquisitions	3,489	4,779	3.02	4.13
Divestments	5,207	5,414	4.29	4.47

Note: The table refers to observed ownership changes (that is, to firms with pre- and post-treatment wage information). Only years relevant to identification are counted before and after the ownership change, e.g. in case of a Domestic-Foreign-Domestic firm for which we observe the foreign acquisition, domestic years before the acquisition and foreign years after the acquisition are included in the table in the respective cells.

Table A2.2b: Number of Firm-Year Observations by Type of Ownership Change – LEED

	Total		Average	
Always Domestic	116,608		3.68	
	Total Before	Total After	Average Before	Average After
Single Acquisitions	1,981	3,062	3.73	5.77
Domestic-Foreign-Domestic				
Acquisitions	336	611	2.92	5.27
Divestments	948	760	4.76	3.84

Note: The table refers to observed ownership changes (that is, to firms with pre- and post-treatment wage information). Only years relevant to identification are counted before and after the ownership change, e.g. in case of a Domestic-Foreign-Domestic firm for which we observe the foreign acquisition, domestic years before the acquisition and foreign years after the acquisition are included in the table in the respective cells.

Table A2.3: Results of Propensity Score Estimation

	Firm-Level Sample	LEED
Log Average Wage	-0.258*	0.237
(Log Average Wage)^2	0.036**	0.000
Log Employment	-0.043**	0.041
(Log Employment)^2	0.014**	0.008
Wage Growth	-0.008	-0.033
Employment Growth	0.075**	0.004
Log Labor Productivity	-0.060	-0.027
(Log Labor Productivity)^2	0.004	0.005
Log Capital Intensity	-0.079**	-0.035
(Log Capital Intensity)^2	0.008**	0.005
Pseudo R^2	0.136	0.244

Note: Marginal effects from probit regressions with treatment status as the dependent variable. That is, the dependent variable equals one if the firm was acquired by foreign owners in a given year, and equals zero for always domestic firms. All variables in the table are lagged and refer to one year before the acquisition. Wage Growth and Employment Growth measure growth rates from two years before acquisition to one year before acquisition. The regressions are pooled, and control firms are weighted so that their weighted number matches the number of treatments each year. We control for industry and year effects. N = 691,243 for the firm-level sample, and 81,639 for the LEED. ** = significant at 0.01; * = significant at 0.05.

Table A2.4: The Effect of Foreign Ownership on Working Hours – LEED, 1999-2008

	FFE	GFE	FWFE
Full Sample			
Acquisition Effect	0.003	-0.006	0.002
	(0.008)	(0.009)	(0.007)
R^2	0.297	0.286	0.410
Matched Sample			
Acquisition Effect	-0.006	-0.018*	-0.002
	(0.009)	(0.008)	(0.008)
R^2	0.325	0.340	0.416

Notes: N = 1,006,100 for the full, and N = 169,263 for the matched sample. The dependent variable is the log of monthly paid hours.

Table A2.5a: Wage Underreporting and Foreign Acquisition – Firm-Level Sample

	FE	Matching with FE
Interactions with Cheating Industry		
Acquisition	0.191**	0.147**
	(0.034)	(0.046)
Acquisition * Non-Cheating Industry	0.111**	0.116*
	(0.040)	(0.054)

Notes: The foreign acquisition dummy is interacted with a dummy variable that equals one for companies operating in two-digit industries with a low wage misreporting index computed by Elek and Szabó (2008). N = 1,806,545 for the full sample, and N = 44,406 for the matched sample.

Table A2.5b: Wage Underreporting and Foreign Acquisition – LEED Sample

	FE	GFE	Matching with FE	Matching with GFE
Interactions with Cheating Industry				
Acquisition	0.135**	0.102**	0.087**	0.106**
	(0.023)	(0.025)	(0.028)	(0.038)
Acquisition * Non-Cheating Industry	0.045	0.036	0.049	0.027
	(0.025)	(0.027)	(0.029)	(0.037)
Proportion of Workers at Minimum Wage				
Acquisition	-0.067**	-0.058**	-0.041**	-0.046**
	(0.011)	(0.012)	(0.007)	(0.009)

Notes: In the top panel, the foreign acquisition dummy is interacted with a dummy variable that equals one for companies operating in two-digit industries with a low wage misreporting index computed by Elek and Szabó (2008). In the bottom panel, we run a linear probability regression where the dependent variable is an indicator for earnings less than 1.03 times the legal minimum wage. FE, GFE and included covariates are the same as in Table 2.13. N = 2,486,269 for the full sample, and N = 395,451 for the matched sample.

Table A2.6: Distribution of Foreign Acquisitions by Source Country

	Firm-Level Sample		LEED	
	Number of Acquisitions	% of Total Acquisitions	Number of Acquisitions	% of Total Acquisitions
Continental Europe	410	23.3	260	54.6
Northern Europe	15	0.9	11	2.3
Southern Europe	32	1.8	23	4.8
United Kingdom, Ireland	32	1.8	19	4.0
USA, Canada	56	3.2	33	6.9
Post-Communist	56	3.2	28	5.9
Offshore	29	1.7	18	3.8
Other	8	0.5	4	0.8
Total	638	36.3	396	83.2

Notes: Source country information is only available for a subset of firms. Continental Europe: Austria, Belgium, France, Germany, Netherlands, and Switzerland; Northern Europe: Denmark, Finland, Iceland, Norway, and Sweden; Southern Europe: Greece, Italy, Portugal, and Spain; Post-Communist: Albania, Bosnia and Herzegovina, Bulgaria, China, Croatia, Czech Republic, Moldova, Poland, Romania, Russia, Slovakia, Slovenia, Ukraine, Yugoslavia, and Vietnam; Offshore: Netherlands Antilles, Bahama Islands, Belize, Cyprus, Gibraltar, Hong Kong, Man Islands, Lichtenstein, Luxembourg, Malta, Panama, Philippines Islands, Seychelles, San Marino, Saint Vincent and Grenada, and Virgin Islands; Other: Botswana, Egypt, India, Israel, Japan, Lebanon, Libya, Singapore, South Korea, South Africa, and Turkey.

CHAPTER THREE

3. Foreign Ownership and the Distribution of Wages in Hungary, 1992-2000: An Unconditional Quantile Decomposition Approach

Abstract

With the help of a rich linked dataset on both firms and workers of the Hungarian corporate sector, this paper analyzes how changes in foreign direct investment contributed to changes in the unconditional wage distribution at different quantiles between 1992 and 2000. After transition, Hungary experienced an extraordinary amount of continuous FDI inflow during the nineties, while earnings inequality increased by close to seventy percent in just ten years, compared to its 1989 level. The role of FDI in inequality changes is partialed out by a detailed decomposition of log wage changes based on a recently developed method by Firpo et al. (2009) that extends the standard Oaxaca-Blinder decomposition to unconditional quantiles of the distribution. I find that at every point in time, the share of employees of foreign-owned firms has a positive and significant wage level effect at every unconditional quantile, and these effects are inequality enhancing for men while they have an ambiguous effect on the unconditional dispersion for women. FDI contributed strongly to wage changes at every part of the distribution through an increased foreign employment share in the economy, but not through changes in the returns to being employed by foreign-owned firms. However, it played only a moderate role in the growth of inequality.

3.1. Introduction

Wage inequality has been one of the most studied topics in all of economic research during the last two decades. Bound and Johnson (1992), Katz and Murphy (1992), Juhn, Murphy, and Pierce (1993), Lemieux (2006) and Autor, Katz, and Kearney (2008) are among the seminal contributions documenting the rise in inequality and some leading explanations behind the trends in the United States. Katz and Autor (1999) summarize the early literature on the U.S. and a few other economies, and Lemieux (2008) provides a recent overview. Both of the last two papers point out that the U.S. economy is a bit of an outlier and that there is significant variation across countries in the extent and patterns of the inequality increase. A rather thinner, but significant, strand of literature focused on the wage effects of foreign ownership – in particular, of foreign acquisitions – to find that in most settings foreign-owned employers pay higher wages on average, keeping everything else constant (e.g. Conyon et al., 2002, Heyman, Sjöholm and Tingvall, 2007, Huttunen, 2007, and Girma and Görg, 2007, among others). This paper is at the intersection of these two areas of labor market research, as it investigates the effect of foreign ownership on the wage distribution as a whole.

Despite vivid interest regarding wage inequality in the U.S., the wage distribution has been carefully studied in rather few countries, with a heavy emphasis on developed economies. In particular, among Central and East European economies, only few thorough studies exist. Keane and Prasad (2006) study the effect of the Polish transition on the structure of earnings, and Ganguli and Terrell (2006) analyze Ukraine. However, the former use data only through 1996, the latter only two cross-sections (1986 and 2003) and both have little information on the employer side. Concerning Hungary, with the exception of the early years of transition (Kertesi and Köllő, 1997), there has been little research on inequality in general, although some aspects of wage differentials have received attention.[71]

[71] For example, Jolliffe and Campos (2004) estimate the effects of market liberalization on the gender wage gap; Kertesi and Köllő study skill differentials (2002) and industrial wage differences (2003a, 2003b); Neumann (2002) explores the effect of collective wage bargaining; Köllő and Nagy (1996) study the effects of unemployment on earnings; and Earle, Telegdy, and Antal (2011) investigate the effects of foreign ownership on average wages and the

It would be profitable to aim at a more pronounced presence of Central and Eastern Europe on the map of earnings inequality research, since the structure of wages in the transition and accession economies of the region have changed dramatically in the last two decades since the collapse of central planning. Real wages tended to decline rapidly in the first few years of transition and to rise strongly more recently, while both overall inequality and estimates of wage differentials associated with human capital show large increases in every country where they have been studied. Following the transition, the tightly controlled wages of the centrally planned systems were abruptly liberalized, permitting organizations to set their own wages and to increase skill differentials, which tended to be compressed under socialism (e.g., Kornai, 1992). At the same time, these countries have experienced massive organizational changes associated with price and trade liberalization, privatization of most types of enterprises, evolution in the institutional environment, and opening to the global economy, particularly to foreign direct investment (FDI).

It is this last factor, the inflow of foreign capital in form of greenfield investments and acquisitions, that the research in this paper is focused at. According to the OECD (2000), during the nineties, Hungary received the largest amount of FDI in the region, and the interest of foreign investors has not languished in the subsequent decade either. The period of fast growth in wage inequality coincided with large-scale privatization and a huge inflow of foreign direct investment, and with the arrival of foreign investors new wage-setting strategies appeared in the country. These rapid changes provide a useful context for investigating the following research questions: Did the ever-increasing inflow of FDI contribute to the dramatic jump in wage inequality? If it did, which parts of the distribution were affected the most heavily? Do we observe a heterogeneous effect similar to the decline in unionization in the U.S., where the impact of changes in the share of union workers was reducing inequality below the median, but widening wage dispersion in the top half of the earnings distribution?[72] Is it only the rise in the foreign share in employment that matters – i.e.

wage structure. The Labor Market Yearbook (2000) contains an overview of the evolution of wages during transition. Preliminary results spanning the entire transition era and the most recent years from an analysis that is concerned with the complete wage distribution show a dramatic increase in the dispersion of earnings, with a rate of growth that was unexperienced even in the U.S. (Antal, 2011).

[72] See for example Firpo, Fortin and Lemieux (2007).

a composition effect –, or was it coupled with a wage structure effect, that is, with a change over time in the labor market return to being employed by foreign owned companies?

Hungary provides a particularly interesting and fruitful case for this analysis, one with the potential to provide lessons of broader importance to scholars interested in a variety of economies. Unlike many other countries of Central and Eastern Europe, the liberalization and privatization processes were relatively quick, and they were largely completed by the early to mid-1990s (e.g., Frydman, Rapaczynski, and Earle, 1993; Mihályi, 1997). Both the ownership structure – the predominance of concentrated outside ownership in large corporations – and the openness of the Hungarian economy quickly became much more similar to developed European economies than elsewhere in the formerly socialist bloc (e.g., Brown, Earle, and Telegdy, 2006). The overall business and policy environment also converged more quickly to European norms, while elsewhere in the region problems of corruption and bureaucratic interference in business tended to be more persistent (e.g., Kaufmann, Kraay, and Mastruzzi, 2003). Hungary, besides having an institutional structure that provides a useful setting for the analysis of wage inequality in transition in general, and of the role of FDI in shaping the wage distribution in particular, also offers a unique database containing linked observations on employees and employers covering the time periods before, during, and after the transition, and containing rich information on both workers and their workplaces.

This paper moves beyond most previous studies of the relationship between foreign direct investment and wages, in estimating the direct contribution of changes in both the distribution of, and the returns to foreign ownership to changes in the unconditional distribution of wages with the help of a recently developed method by Firpo, Fortin and Lemieux (2007, 2009). To estimate this contribution, any method has to capture two effects of FDI that might work at the same time. The first is a between-group effect represented by the difference in mean wages of otherwise comparable employees of foreign and domestic firms. The second is a within-group effect that is generated by potential differences in conditional foreign wage premia at different quantiles of the conditional wage distribution of worker groups defined by individual characteristics other than foreign control. Running usual conditional quantile regressions would only capture this latter effect, while the major part of the literature on FDI and wages focuses on the first one. Firpo, Fortin and Lemieux (2009) merge the concepts of influence functions and quantile regressions to be able to estimate the partial effect of changes in covariates on the unconditional quantiles of the wage distribution. This regression framework is then extended by Firpo, Fortin and Lemieux (2007) to decompose changes in the unconditional wage quantiles over time and measure the contributions of single covariates through a composition and a wage structure channel which are both allowed to be heterogeneous across quantiles.

3.2. Foreign Ownership and Wage Dispersion: Current State of Knowledge

Studies of wage inequality typically exclude peculiarities of employers and concentrate on individual characteristics of the worker, like education, experience, occupation and gender. Usually, region and industry controls are also involved in the analysis, however, these are rather indicators for heterogeneity in labor markets and not for heterogeneity of firms. One notable exception that received a lot of attention in the wage inequality literature on the U.S., and that might be viewed as both a worker and a firm attribute, is union status.[73]

Including firm characteristics when examining changing patterns of wage dispersion might be fruitful ex ante for at least two reasons. First, an emerging strand of literature delivered evidence on the substantial role of between-establishment wage dispersion in shaping the overall distribution of wages.[74] Second, a large chunk of the rise in wage inequality is still unaccounted for even after controlling for the usual suspects for possible explanations like skill-biased technological change, import competition, worker composition effects, and changes in labor market institutions, such as the minimum wage legislation and the degree of unionization.[75]

[73] See DiNardo, Fortin and Lemieux (1996), Firpo, Fortin and Lemieux (2007, 2009) and DiNardo and Lemieux (1997). In the paper, I rely mostly on methods that were developed in this series of studies addressing the impact of deunionization on wage inequality.
[74] Among others, Davis and Haltiwanger (1991), Abowd, Kramarz, and Margolis (1999), Dunne et al. (2004), Haltiwanger, Lane and Spletzer (2007).
[75] Skill endowments and skill prices, account only for a small fraction of both the level and the change in overall wage inequality. Juhn, Murphy, and Pierce (1993) find that in the U.S., unobserved skill quantities and prices account for 56% of the total growth in the log 90-10 wage differential of men, between 1964 and 1988. Autor, Katz, and Kearney (2005) show that the same measure is 63% in the 1988-2003 period.

Turning to the literature on FDI and wages, the relationship between foreign ownership and average wages has been investigated to a large extent, but the same is not true for other moments of the wage distribution. Authors using firm-level data typically find a positive foreign premium regarding the conditional expectation of wages,[76] while a smaller fraction of papers based on linked employer-employee data tend to find a smaller or even a zero causal effect after controlling for various individual and firm characteristics, and for unobserved heterogeneity as much as the data permit to do so – with the exception of Hungary, where the effect is large even in the linked sample.[77] Note that in the case of the first moment, studies concerned with the causal effects of foreign acquisitions and/or divestments on the conditional expectation of wages implicitly estimate an unconditional effect, too. It can be shown that in an OLS regression, the estimated coefficient on the foreign dummy has a dual interpretation: it gives the expected return to a worker employed by a foreign firm relative to a worker with similar characteristics employed by a domestic firm; but it also measures the marginal effect of an increase in the share of foreign employment on the unconditional mean of wages.[78] Still, this does not tell us anything about a possible change in the shape of the unconditional distribution of wages.

Of course, a difference in average wages at the firm-level between domestic and foreign firms contributes directly to between-firm wage inequality and thus to overall inequality as well, but mostly, the focus of these studies is to disentangle spurious correlation and causal effects, and to measure a "true" foreign wage premium and not to quantify the contribution to inequality. Furthermore, as discussed in Section 1, the difference in conditional first moments is only a between-group effect on the unconditional wage distribution, but there might be another, within-group effect potentially implying different conditional wage premia at different points of the conditional wage distribution. To evaluate the impact of foreign ownership on the unconditional

[76] Firm-level studies include Conyon et al. (2002), and Girma and Görg (2007), both on the UK; Aitken, Harrison, and Lipsey (1996) on Mexico, Venezuela, and the US; Feliciano and Lipsey (2006) on the US; Lipsey and Sjöholm (2004) on Indonesia; and Brown, Earle and Telegdy (2008) on FDI entry through privatization in Hungary, Romania, Russia, and Ukraine.
[77] See Martins (2004) and Almeida (2007) for Portugal; Heyman et al. (2006, 2007) for Sweden; Huttunen (2007) for Finland; Andrews et al. (2007) for Germany; Martins and Esteves (2008) for Brazil; and Earle, Telegdy, and Antal (2011) for Hungary.
[78] This is only true if the foreign dummy enters the regression independently, i.e. not interacted with other covariates, otherwise one has to integrate over the distribution of other covariates to get to the unconditional interpretation.

wage dispersion, one has to estimate these two effects simultaneously that can be performed in an unconditional quantile regression framework applied later in the paper.

There are some recent studies that move beyond the relationship of FDI and the conditional grand mean of wages. However, in most cases, the analysis is only extended to wage structure effects in that the work force is divided into a few skill groups, and the authors estimate foreign wage premia separately for each of these. For example, Huttunen (2007) examines how the foreign acquisition wage effect varies by educational groups of Finnish plants and finds that the magnitude is increasing with the level of schooling. Almeida (2007) shows that after controlling for selection, foreign acquisitions result in only modest wage gains for Portuguese workers, but the difference is increasing in skill. Eriksson and Pytliková (2011), studying a single cross-section of Czech linked employer-employee data, disaggregate workers into white-collar and blue-collar employees and find that FDI benefits both groups, with a higher average wage gain for the former group.[79] These studies all estimate a price effect of FDI on the wage distribution, but since the focus is not on quantifying to exactly what extent changes in the ownership structure contributed to changes in the wage distribution, they ignore the composition effect and the time dimension.

Following a different approach, Eriksson, Pytliková and Warzynski (2009) look at the evolution of within-firm and between-firm inequality in the Czech Republic, and find a quite robust positive effect of foreign ownership on both. However, they only have data for the 1998-2006 period, and thus lose valuable information on early-transition years, where the most important changes affecting the wage structure presumably happened. Also, their dependent variables are the within-firm and between-firm conditional standard deviation of wages, so they do not answer the question how the inflow of foreign capital affected dispersion in the unconditional distribution. As noted earlier, this research contributes to the literature by shedding light on this latter aspect of the relationship between FDI and labor market outcomes.

[79] Using Swedish data, Heyman, Sjöholm and Tingvall (2006) distinguish three skill groups, and find – somewhat surprisingly – that foreign acquisitions result in wage growth only for the top occupational groups, in particular for CEOs and managers, moreover, it seems to be a consequence of acquisition, and not a genuine foreign effect. In contrast, Earle, Telegdy and Antal (2011) estimate the foreign wage structure effect in Hungary, by interacting the foreign acquisition dummy with various individual characteristics and show that every worker group experiences an increase in average wages, with extra premia for the high-educated.

3.3 Description of Data

The main body of data used in this paper comes from the Hungarian Wage Survey (HWS), a yearly survey on employees – augmented with some information on the employer – conducted by the Central Statistical Office. To assemble the linked employer-employee dataset (LEED) necessary for the analysis, the worker-level HWS files are linked with the help of a firm identifier to administrative firm-level data collected by the Hungarian Tax Authority (HTA). The HTA database contains the complete balance sheet and income statement of firms with double-entry book keeping in the Hungarian business sector. The inclusion of employers in the HWS based on their size has changed over the years. All business units were surveyed in 1986, 1989; the size threshold of sample inclusion was at least 20 employees between 1992 and 1995; a random sample of firms with 11-20 employees was added to the group of larger firms between 1996 and 1999, which was extended to the threshold of 5 employees thereafter. Since the foreign share of firms varies by size, and the size distribution of firms is truncated at different points in different years, I only include firms with more than 20 employees in any given year to insure sample consistency. Within business units, workers were sampled representatively, based on a random sampling design.[80] The linked data are a panel in firms, but not in workers, although it is possible to follow the majority of individuals that do not change employers over time exploiting the birth-date-based sampling design and the rich set of observed characteristics.

I use two sets of sample weights. The first is a within-establishment and within-occupational-group worker weight to account for the different degree of representation of the blue- and white-collar workers within establishments. The second is a company-level multiplier that weights up the sample to the total employment of the corporate sector of Hungary. The final sample weight is the product of the individual and the firm weights. In addition, whenever it is

[80] In 1986 and 1989, all senior managers were included, and a random sample of the rest of the professionals was selected on the basis of the socialist wage grid; the first and every fifth employee in 1986 and every tenth in 1989. In case of manual workers, the survey covered the first and then every seventh worker of each wage group in 1986, while the first and every tenth person in 1989. In 1992 and 1993, every blue-collar worker born on the 5th or 15th of any month and every white-collar worker born on the 5th, 15th or 25th was surveyed. This scheme was maintained after 1993 for firms above a certain size threshold, and all employees' information were required from sampled companies smaller than the threshold. The size limit was 20 employees from 1994 to 2001, and it was raised to 50 employees thereafter.

necessary for constructing counterfactual samples, I weight observations by probability weights that rescale the actual distribution of individual characteristics. How these weights are estimated, is described in detail in Section 4. Of course, once applied, probability weights are always multiplied by sample weights.

The HWS contains information on earnings and its various components (e.g., basic wage, bonuses, temporary payments, commissions, allowances), working hours, demographic and human capital variables, four-digit occupation codes and plant-level location information. From the HTA data, I use information on equity share to construct a foreign ownership dummy, and industrial affiliation. The data were cleaned both at the individual- and the firm-level extensively. Variable definitions and classifications are harmonized over time, with special attention to the synchronization of the pre- and post-transition parts of time series. The common issue of spurious firm entry and exit was addressed with the help of another dataset that provides administrative information on boundary changes, entry and exit. Exit and entry rates were improved by detecting more than 3,000 erroneous identifier changes.

The main variable of interest, ownership, was carefully cleaned both at the share level, and after defining ownership dummies based on relative equity shares. At the share level, "roundtripper" observations – where shares switch owners for a single year – were recoded, and impossible changes – like the increase in state ownership shares – were cleaned where possible, or were set to missing. I use a simple majority definition of foreign ownership, that is, the firm is considered to be foreign owned if at least fifty percent of its equity is owned by foreign investors. Roundtrippers were also cleaned at the dummy level, and I filled up missing values in the middle of long series of the same owner type. Of the sample of firms with more than 20 employees, I dropped 855 which experience more than two changes in ownership status because in general these tend to have unreliable ownership data.

I excluded part-time employees since they are only observed after 2002, and I only kept individuals with an age of more than 15 and less than 74 years. Two-digit industries that do not have any foreign presence at all are excluded from the analysis (NACE 42 and 91), as well as

NACE codes 75, 80 and 85 (public administration). The final sample comprises 2.5 million worker-year observations, and a total of 25,000 unique firms, covering two decades between 1986 and 2008. I present the evolution of inequality for all these years, but I only investigate the effect of foreign ownership for the period between 1992 and 2000, the decade of the largest increase in wage dispersion. Table 3.1 summarizes by-year information about sample sizes and the degree of representation. On average, the sample includes 100,000 workers per year, representing 1.1 million employees. The third column shows that this is close to seventy percent of total employment by enterprises with more than 20 employees, as measured by the sum of employment of these firms in the HTA dataset. I demonstrate in Figure 3.1 that the linked sample is also doing a very good job in tracking down patterns of foreign ownership shares in both number of firms and number of employees in the full business sector data. In terms of number of firms, foreign penetration reaches 20 percent by 2008, while the share in total employment is close to 40 percent among companies above the 20-employee limit.

3.4. Estimation Methods

The ultimate goal of decomposition exercises is to quantify the effect of changes in the composition of observable and unobservable factors, and the effect of changes in labor market returns to these factors (or in other words, changes in the wage structure) on the unconditional distribution of wages. That is, we aim to decompose the overall change in some functional $\nu(G_w)$ of the unconditional wage distribution characterized by the CDF $G_w(.)$, into a factor due to underlying changes in the composition of individual characteristics, and into a factor due to changes in the wage structure where the set of individual characteristics might include both observable and unobservable elements, and by wage structure we might think of a process that rewards both types of characteristics. This is called an aggregate decomposition in the literature,[81] and is given by $\Delta_O^{\nu(G)} \equiv \Delta_C^{\nu(G)} + \Delta_S^{\nu(G)}$, where the left-hand side is the overall difference in some distributional attribute of wages between two states (e.g. worker groups or periods of time), and the

[81] For an exhaustive survey of decomposition methods see Fortin, Firpo and Lemieux (2011). I follow to a great extent their notation and terminology in this paper.

first term of the sum represents composition effects while the second the wage structure effects.[82] In most applications, however, we are interested in the contribution of some individual characteristic of interest to both the composition and the wage structure effects – as in this paper, I want to quantify the contribution of foreign ownership –, so we would like to further decompose $\Delta_C^{\nu(G)}$ and $\Delta_S^{\nu(G)}$ by means of a detailed decomposition.

To perform decompositions, counterfactual states of the world have to be constructed keeping one or more factors fixed while letting the others change to partial out their effect. The aim of this paper is to partial out the composition and wage structure effects of foreign ownership. The related counterfactual exercises are of the form: How would the distribution of wages look like in some end period if every factor was kept at some base period's level except the proportion of workers employed by foreign-owned companies (or alternatively, the returns to being employed by a foreign-owned company)? The difference between an actual unconditional wage distribution, and the counterfactual wage distribution gives either the composition or the wage structure effect of foreign investment, depending on what dimension of foreign ownership was allowed to change over time.

Once the counterfactual and actual distributions are specified and identifying assumptions are set, one can estimate either the corresponding distributions non-parametrically, or various functionals of the distributions (like quantiles, the variance and other inequality measures) with the help of a parametric model. I will both decompose densities of wages, and quantiles and interquantile ranges of wage distributions to estimate the contribution of foreign ownership to changes in wage inequality. In section 4.1, I briefly summarize the reweighting decomposition method of DiNardo, Fortin and Lemieux (1996) and of DiNardo and Lemieux (1997) – DFL and DL henceforth – which I apply to construct counterfactual densities and to perform density

[82] Consider the case of the well-known mean decomposition proposed in the seminal papers of Oaxaca (1973) and Blinder (1973). In their method, $\nu(G)$ equals μ, the unconditional mean of wages, and the wage generating process is assumed to be $w = X\beta + \varepsilon$, where X is a vector of observed characteristics and ε is an idiosyncratic error term. Then, after setting some identifying assumptions, the estimated OB decomposition in its simplest form between two groups 1 and 2, is given by $\Delta_O^{\mu} \equiv \Delta_X^{\mu} + \Delta_S^{\mu} = (\bar{X}_1 - \bar{X}_2)\hat{\beta}_1 + \bar{X}_2(\hat{\beta}_1 - \hat{\beta}_2)$, where $\bar{X}$-s are sample averages and β-s are estimated by OLS. It is also straightforward to compute the contribution of each element in X to both parts of the decomposition.

decompositions.[83] The DFL method is designed to identify composition effects, while the DL method is an extension to identify wage structure effects. In section 4.2, I describe the procedure recently developed by Firpo, Fortin and Lemieux (FFL, 2007) that combines reweighting and recentered influence function (RIF) regressions to decompose quantiles and inequality measures.

3.4.1. Counterfactual Wage Distributions

As I examine changes in the wage distribution over time, between two periods, let $t = \{b, e\}$ denote time, where b refers to some base period, and e to some end period. Log wages w are determined at any point in time by the wage structure function, $w_t = s_t(X, \varepsilon)$,[84] where $X = [X_i]_{i=1}^{k} = [f, Z]$ is a vector of worker and firm characteristics with $X_1 = f$ denoting the foreign ownership dummy, and $Z = [Z_i]_{i=2}^{k}$ the rest of covariates, such as education, gender, occupation, potential experience, region of workplace and industrial affiliation of the employer; while ε measures unobserved individual heterogeneity.[85] Let $G_{X,t}(X)$ denote the (marginal) cumulative distribution function of covariates in t, while $G_{w|X,t}(w|X)$ the conditional, and $G_{w,t}(w)$ the unconditional CDF of wages in t. Let $g_t(.)$ refer to the corresponding densities, for example, $g_{w,t}(w) = \frac{dG_{w,t}(w)}{dw}$.

The unconditional density of log wages in time t can be written as

(1) $$g_{w,t}(w) = \int g_{w|X,t}(w|X)\, dG_{X,t}(X) = \int g_{w|X,t}(w|f, Z)\, dG_{X,t}(f, Z).$$

Since the joint distribution of covariates, $G_{X,t}(f, Z)$, can be expressed as $G_{f|Z,t}(f|Z)G_{Z,t}(Z)$, equation (1) turns into

(2) $$g_{w,t}(w) = \iint g_{w|X,t}(w|f, Z)\, dG_{f|Z,t}(f|Z) dG_{Z,t}(Z).$$

[83] The DFL method was used in other areas of labor market research, too. The original work by DiNardo, Fortin and Lemieux (1996) and the follow-up by DiNardo and Lemieux (1997) examine how changes in the unionization level in the U.S. and Canada affect the distribution of wages. In the context of transition, Lehmann and Wadsworth (2007) look at the effect of wage arrears on the Russian wage distribution by constructing counterfactual densities with DFL reweighting.

[84] Since this subsection is about the non-parametric estimation of densities, I will only specify the form of the wage structure function in subsection 4.2.

[85] To simplify the discussion in this section, all characteristics of the employer are considered as individual characteristics of the employee.

One counterfactual distribution of interest is the hypothetical distribution of wages that would prevail if the proportion of workers employed by foreign-owned firms was fixed at its base period level, but other individual attributes, and the conditional density of wages were allowed to change to their end period values. Let the asterisk in the upper index always denote counterfactual states, then we have the following counterfactual density of wages for the composition effect exercise (marked by upper index C):

(3) $$g_{w,e}^{*,C}(w) = \iint g_{w|X,e}(w|f,Z)\, dG_{f|Z,b}(f|Z)\, dG_{Z,e}(Z).$$

Note that this formulation implicitly involves a very strong assumption called the invariance of conditional distributions by Fortin, Lemieux and Firpo (2011). By equation (3), we are ruling out self-selection into foreign ownership status based on ε, as well as general equilibrium (or spillover) effects of foreign investment, since these are both assumed away by leaving the conditional distribution of wages unaffected while changing the distribution of foreign ownership.

Following the DFL technique, the conditional base period distribution of foreign ownership can be substituted by properly reweighting its end period conditional distribution to get

(4) $$g_{w,e}^{*,C}(w) = \iint g_{w|X,e}(w|f,Z)\, \Psi^C(f,Z)\, dG_{f|Z,e}(f|Z)\, dG_{Z,e}(Z),$$

where the reweighting function is

(5) $$\Psi^C(f,Z) \equiv \frac{dG_{f|Z,b}(f|Z)}{dG_{f|Z,e}(f|Z)} = f \cdot \frac{Pr_b(f=1|Z)}{Pr_e(f=1|Z)} + (1-f) \cdot \frac{Pr_b(f=0|Z)}{Pr_e(f=0|Z)}.$$

The main advantage of this formulation is that the conditional probabilities of ownership status $Pr_t(f = 1|Z)$ and $Pr_t(f = 0|Z)$ can be readily estimated by specifying a probit or logit model for the probability of being employed by a foreign-owned company conditional on Z in both periods. The predicted probabilities are then used to estimate $\widehat{\Psi}^C(f,Z)$ for every observation of the end period.

The contribution of foreign ownership to the composition effect of X on the change in the unconditional density of log wages is then given by the difference between the actual unconditional density of log wages in the end period, and the counterfactual density defined by equation (4). That is

(6) $$\Delta_{C_f}^{g(w)} \equiv g_{w,e}(w) - g_{w,e}^{*,C}(w).$$

To demonstrate the wage structure effect of a binary variable on the density of wages, DiNardo and Lemieux (1997) follow a different path, but applying a similar reweighting procedure that led to expression (6) for the composition effect. The hypothetical state of the world we would need is one where every worker was paid under the wage structure of domestic companies. The distribution of wages in this state for period t could be constructed as

(7) $$g_{w,t}^{*,S}(w) = \int g_{w|X,t}(w|f = 0, Z)\ dG_{Z,t}(Z).$$

Now since we do not observe the wage structure, $g_{w|X,t}(w|f = 0, Z)$**,** for workers of foreign firms, we cannot estimate the counterfactual density in this form. Thus, DiNardo and Lemieux suggest reweighting the sample of domestic workers so that the distribution of Z in this subsample reflects the distribution in the entire sample. Applying Bayes' Law, we can write

(8) $$G_{Z,t}(Z) = \frac{G_{Z|f,t}(Z|f=0) \cdot Pr_t(f=0)}{Pr_t(f=0|Z)} = G_{Z|f,t}(Z|f = 0) \cdot \Psi_t^S(Z),$$

where $\Psi_t^S(Z)$ denotes the reweighting function used for the wage structure effect exercise. It can be estimated the same way as $\Psi^C(f, Z)$ by running a binary outcome regression for $Pr_t(f = 0|Z)$, and by replacing $Pr_t(f = 0)$ by the proportion of workers in the sample employed by domestic companies. The estimable counterfactual density is given by

(9) $$g_{w,t}^{*,S}(w) = \int g_{w|X,t}(w|f = 0, Z)\ \Psi_t^S(Z)\ dG_{Z|f,t}(Z|f = 0),$$

and is only estimated for the subsample of domestic workers.

Note that the expression in (9), including the reweighting function, is time dependent, since the counterfactual thought experiment is different by nature from the one for the composition effect. Nevertheless, we can define the wage structure effect of foreign ownership on the density of wages over time by

$$(10) \qquad \Delta_{S_f}^{g(w)} \equiv \left[g_{w,e}(w) - g_{w,e}^{*,S}(w)\right] - \left[g_{w,b}(w) - g_{w,b}^{*,S}(w)\right].$$

The interpretation of definition (10) is that once we know the part of the observed density of wages that can be attributed to the different pay schemes of foreign and domestic employers in both periods, the wage structure effect of foreign ownership on changes in the wage distribution is simply the difference of these two parts.

The only missing element is the estimation of the actual and the counterfactual densities. In the first step, I obtain $\widehat{\Psi}^C(f,Z)$ and $\widehat{\Psi}_t^S(Z)$ as described above, and in the second step, densities are estimated by a kernel density estimator of the form

$$(11) \qquad \hat{g}_{w,t}(w) = \frac{1}{h\sum\omega_i}\sum\omega_i\, K\left(\frac{w-W_i}{h}\right) \quad \text{and}$$

$$(12) \qquad \hat{g}_{w,t}^{*}(w) = \frac{1}{h\sum\omega_i}\sum\omega_i\, \widehat{\Psi}(.)\, K\left(\frac{w-W_i}{h}\right),$$

where ω_i are sample weights, h is the bandwidth of the kernel, $K(.)$ is the Epanechnikov kernel function, while $\widehat{\Psi}(.)$ denotes either $\widehat{\Psi}^C(f,Z)$or $\widehat{\Psi}_t^S(Z)$, depending on which counterfactual density we would like to estimate.

3.4.2. Decomposition Based on Unconditional Quantile Regressions

Section 4.1 was instructive as (i) it showed how the DFL reweighting approach works in general, (ii) it proposed a tool for visually inspecting the difference between actual and properly defined counterfactual densities to get a hint about the nature of foreign composition and wage structure effects, and (iii) it provides a basis for decomposing any usual distributional statistic or inequality measure. The last point is straightforward, because once we estimated the densities non-parametrically; interquantile differentials, the variance, the Gini coefficient or other measures of dispersion can be computed. However, the method has an important limitation: the generalization to more and to non-binary covariates is cumbersome, especially in case of the wage structure effect.[86] This is why I will work with a hybrid method proposed by Firpo, Fortin and Lemieux

[86] See more about the advantages and limitations of the DFL method versus other approaches in Fortin, Lemieux and Firpo (2011).

(2007) that combines DFL reweighting and a method called recentered influence function (RIF) regression to perform detailed decompositions similar to a standard OB decomposition on quantiles and inequality measures. The FFL decomposition is easy to implement, has good asymptotic features, is straightforward to interpret,[87] and is computationally feasible for large datasets such as the LEED used in this paper.[88] First, I describe the concept of RIF regressions, as introduced by Firpo, Fortin and Lemieux (2009), and then the decomposition method that builds on RIF projections and DFL reweighting.

The main goal of a detailed quantile decomposition is to quantify the effect of covariates on various parts of the wage distribution. Thus, the RIF idea is based on the concept of the influence function, a tool introduced in the robust estimation literature by Hampel (1974) to measure the effect of small perturbations of an underlying distribution on functionals – e.g. quantiles – of the distribution. The influence function (IF) of the functional $\nu(G_w)$, for the underlying wage distribution $G_w(w)$ is defined as:

(13) $$IF(w,\nu,G_w) \equiv lim_{h\to 0}\frac{\nu(G_{w,h\cdot\Delta_w})-\nu(G_w)}{h} = \frac{\partial\nu(G_{w,h\cdot\Delta_w})}{\partial h}|_{h=0},$$

where $G_{w,h\cdot\Delta_w} = (1-h)G_w + h\Delta_w$ is the perturbed wage distribution with the point mass distribution Δ_w at w. We are in general interested in what happens to the functional not in the case of a point-mass perturbation, but if the distribution G_w moves towards a new distribution, G_w^*. For that, we need the directional derivative of $\nu(G_w)$, in the direction of G_w^*, or, a function called the integrated IF by Cowell and Victoria-Feser (1993).

(14) $$IIF(\nu,G_w) \equiv \frac{\partial\nu(G_{w,h\cdot G_w^*})}{\partial h}|_{h=0} = \int IF(w,\nu,G_w)\, d\,(G_w^* - G_w)(w) =$$

$$= \int IF(w,\nu,G_w)\, d\,G_w^*(w),$$

[87] Except for wage structure effects that suffer from the same omitted group problem as the OB decomposition.
[88] This is probably the biggest advantage over conditional quantile methods like the one in Machado and Mata (2005), which is basically impossible to implement with reasonable computing resources for datasets larger than a few thousand observations.

where the perturbed distribution is now $G_{w,h\cdot G_w^*} = (1-h)G_w + hG_w^*$, and the last equality holds because $\int IF(w,\nu,G_w)\, d\, G_w(w) = 0$, by definition. The IIF's interpretation as a directional derivative is important intuitively, since it is suitable to determine the approximate value that functional $\nu(.)$ takes on when $G_w(w)$ is perturbed by h times $G_w^*(w)$. More formally, using a local first-order Taylor approximation:

(15) $$\nu\left(G_{w,h\cdot G_w^*}\right) \approx \nu(G_w) + h \cdot IIF(w,\nu,G_w)$$

Now define the recentered influence function (RIF) by adding back the IF to the original functional of the distribution, that is

(16) $$RIF(w,\nu,G_w) \equiv \nu(G_w) + IF(w,\nu,G_w).$$

The RIF has the convenient feature that its expectation is equal to $\nu(G_w)$. Moreover, it is easy to show that (14) also holds for the RIF, such that

(17) $$\frac{\partial \nu\left(G_{w,h\cdot G_w^*}\right)}{\partial h}\Big|_{h=0} = \int RIF(w,\nu,G_w)\, d\,(G_w^* - G_w)(w).$$

Now assume that the perturbation is caused by a change in the distribution of some underlying worker characteristics. The unconditional distribution of wages can be expressed as in (1) in terms of the conditional distribution of wages given the covariates, and the marginal distribution of the covariates as

(18) $$G_w(w) = \int G_{w|X}(w|X)\, dG_X(X).$$

Again, assuming invariance of the conditional distribution to changes in the distribution of X, the perturbed (counterfactual) distribution of wages is given by

(19) $$G_w^*(w) = \int G_{w|X}(w|X)\, dG_X^*(X),$$

where the perturbation in $G_w^*(w)$ is now due to a perturbation in the distribution of the covariates, $G_X^*(X)$. By plugging into (17), and applying the law of iterated expectations we get

(20) $$\frac{\partial \nu\left(G_{w,h\cdot G_w^*}\right)}{\partial h}\Big|_{h=0} = \int \mathbb{E}[RIF(w,\nu,G_w)|X=x]\, d\,(G_X^* - G_X)(x).$$

Remember that X stands for a vector of k covariates, $[X_i]_{i=1}^{k}$, distributed as G_X. Consider now a ceteris paribus location shift in the jth covariate, so that the new set of covariates X^h is equal to $\left[X_i^h\right]_{i=1}^{k}$, $X_i^h = X_i$ for $i \neq j$, and $X_i^h = X_i + h$ for $i = j$. Let the distribution of X^h be denoted by the perturbed distribution, G_X^*. It can be derived that the unconditional distribution of wages will then be $G_{w,h \cdot G_w^*} = (1-h)G_w + hG_w^*$. The central theorem in Firpo, Fortin and Lemieux (2009) states that the local effect of a location shift in one of the covariates on some functional of the unconditional distribution of wages, keeping the other covariates constant, is given by

(21) $$\frac{\partial \nu\left(G_{w,h \cdot G_w^*}\right)}{\partial h}\Big|_{h=0} = \int \frac{\partial \mathbb{E}[RIF(w,\nu,G_w)|X=x]}{\partial x_j} \, d\, G_X(x).$$

In other words, one can express the ceteris paribus effect of the change in the distribution of a covariate on any distributional statistic by the average partial effect of that covariate on the conditional expectation of its recentered influence function. So once a functional form is specified for the conditional expectation of the RIF, usual regression methods can be used to estimate the average partial effect. Firpo, Fortin and Lemieux (2009) discuss in detail the choice of the functional form; in this paper, I will assume that the conditional expectation is linear – that is $\mathbb{E}[RIF(w,\nu,G_w)|X=x] = X\beta$ –, but I will account for the possible specification error when performing the decomposition.

It is easy to see that to estimate the effect of changes in the distribution of worker characteristics on some functional of the unconditional distribution of wages – e.g. the variance, the median or other quantiles –, one only has to determine the RIF corresponding to that particular functional at every observed wage in the sample, and regress the RIF values on individual characteristics. For example, it is possible to answer the question how the increase in the share of workers employed by foreign-owned companies affected certain quantiles of the unconditional wage distribution.

The RIF of the τth quantile, q_τ, of the unconditional distribution of wages is calculated as

(22) $$RIF(w,q_\tau,G_w) = q_\tau + \frac{\tau - \mathbb{I}\{w \leq q_\tau\}}{g_w(q_\tau)},$$

where $\mathbb{I}\{.\}$ is an indicator function. An estimate for (22) is obtained by estimating q_τ by the sample quantile, and the corresponding density, $\hat{g}_w(\hat{q}_\tau)$, by a kernel density estimator. Note that due to the presence of the indicator function in (22), in case of quantiles, assuming a linear functional form for $\mathbb{E}[RIF(w, q_\tau, G_w)|X]$ effectively means estimating a linear probability model, where the dependent variable is the estimated RIF and the covariates are individual characteristics of interest.[89]

With $\mathbb{E}[RIF(w, q_\tau, G_w)|X]$ specified, it is straightforward to adapt the standard OB decomposition framework to the RIF regressions. As noted earlier in the section, wages in year t are generated by the wage structure function $w_t = s_t(X, \varepsilon)$. The standard OB framework hinges on the assumption of linear additive separability, that is, $w_t = s_t(X, \varepsilon) = X_t\beta_t + \varepsilon_t$. Then the overall change in the unconditional mean of wages between years e and b, $\Delta_O^\mu = \mathbb{E}(w|t = e) - \mathbb{E}(w|t = b)$, is equal to $\mathbb{E}(X|t = e)\beta_e - \mathbb{E}(X|t = b)\beta_b$ under the additional assumption of $\mathbb{E}(\varepsilon_t|X) = 0$, and by applying the law of iterated expectations. The difference can be then decomposed by adding and subtracting the counterfactual expected wage when workers in year b earn the returns that prevail in year e:

$$(23) \qquad \Delta_O^\mu = [\mathbb{E}(X|t = e) - \mathbb{E}(X|t = b)]\beta_e \; + \; \mathbb{E}(X|t = b)(\beta_e - \beta_b) =$$
$$= \quad \Delta_C^\mu \qquad + \qquad \Delta_S^\mu,$$

where the first term is the aggregate composition (or explained) effect and the second term is the aggregate wage structure (or unexplained) effect. Estimates for the composition and wage structure effects are obtained by replacing $\mathbb{E}(X|t)$-s by sample averages, and β_t-s by OLS estimates.

Returning to the RIF quantile regression framework, the argument goes along the same lines, but the starting points are modified to the overall effect $\Delta_O^{q_\tau} = \mathbb{E}(RIF(w, q_\tau, G_w)|t = e) - \mathbb{E}(RIF(w, q_\tau, G_w)|t = b)$, and to the data generating process $RIF_t(w, q_\tau, G_w) = X_t\beta_t^{(\tau)} + \varepsilon_t^{(\tau)}$, for

[89] Firpo, Fortin and Lemieux (2009) discuss alternative estimation methods of the average partial effects, such as the logit and a non-parametric method. As noted earlier, I will assume that the LPM estimates the partial effects consistently. Note that it is necessary to assume linearity for carrying out the detailed decomposition, but I will account for possible specification errors by reweighting.

every quantile of rank τ in year t. The expectations and the coefficients can be estimated the same way as in the case of the OB method.

Barsky et al. (2002) pointed out that the classical OB decomposition will be inconsistent if the expectation $\mathbb{E}(w|X,t)$ is not linear. This is also true in case of the RIF decomposition. Fortin, Lemieux and Firpo (2011) propose to use the DFL reweighting method to account for possible specification biases in the decomposition. To see this, first let us construct the counterfactual distribution of wages when the distribution of year e characteristics is reweighted so that it resembles the distribution in year b. That is, we need

$$(24) \qquad G_{w,e}^{*}(w) = \int G_{w|X,e}(w|X)\, \Psi^{e}(X) dG_{X,e}(X),$$

and the reweighting factor is shown by DiNardo, Fortin and Lemieux (1996) to be

$$(25) \qquad \Psi^{e}(X) = \frac{dG_{X,b}(X)}{dG_{X,e}(X)} = \frac{Pr(X|t=b)}{Pr(X|t=e)} = \frac{Pr(t=b|X)\cdot Pr(t=b)}{Pr(t=e|X)\cdot Pr(t=e)},$$

where the last equality follows from Bayes' Law. The estimate, $\widehat{\Psi}^{e}(X)$, is obtained by pooling data from the base and end periods, and estimating a binary outcome model for either $Pr(t=b|X)$, or for $Pr(t=e|X)$, and multiplying the predicted conditional probabilities by the share of observations in the respective period.[90] The counterfactual expectation of wages is then estimated by sample averages in the reweighted sample of year e, multiplied by OLS estimates of labor market returns from a reweighted regression of RIF values on covariates, that is, $\mathbb{E}^{*}(X|t=e)\beta_{e}^{*} \xrightarrow{est} \bar{X}_{e}^{*}\hat{\beta}_{e}^{*}$.

The decomposition is now given by the difference between actual averages and the reweighted counterfactual average as

$$(26) \qquad \hat{\Delta}_{O}^{q_\tau} = \hat{\Delta}_{C}^{q_\tau} + \hat{\Delta}_{S}^{q_\tau} = \left(\bar{X}_{e}\hat{\beta}_{e}^{(\tau)} - \bar{X}_{e}^{*}\hat{\beta}_{e}^{*(\tau)}\right) + \left(\bar{X}_{e}^{*}\hat{\beta}_{e}^{*(\tau)} - \bar{X}_{b}\hat{\beta}_{b}^{(\tau)}\right),$$

which can be further decomposed into "true" composition and wage structure effects and error terms by

[90] Obviously, since the subsamples for the two periods are mutually exclusive, $Pr(t=b|X) = 1 - Pr(t=e|X)$, and $Pr(t=b) = 1 - Pr(t=e)$.

(27) $$\hat{\Delta}_C^{q_\tau} = (\bar{X}_e - \bar{X}_e^*)\hat{\beta}_e^{(\tau)} + \left(\hat{\beta}_e^{(\tau)} - \hat{\beta}_e^{*(\tau)}\right)\bar{X}_e^* \quad \text{and}$$

(28) $$\hat{\Delta}_S^{q_\tau} = \bar{X}_b\left(\hat{\beta}_e^{*(\tau)} - \hat{\beta}_b^{(\tau)}\right) + (\bar{X}_b - \bar{X}_e^*)\hat{\beta}_e^{*(\tau)}.$$

In both expressions, the first term represents the pure composition/wage structure effect. Within (29), $\left(\hat{\beta}_e^{(\tau)} - \hat{\beta}_e^{*(\tau)}\right)\bar{X}_e^*$ reflects the specification (or approximation) error that arises if the conditional expectation of the RIF is not linear, and it also captures errors from the fact that RIF regressions are based on local approximations of unconditional wage effects. If the specification error is found to be small, it is indicative of the RIF regression doing a good job in estimating the effects of large shifts in the distribution of covariates. It is especially important to check this term in the context of this paper, since the share of workers employed by foreign firms increased at a high rate over the years. $(\bar{X}_b - \bar{X}_e^*)\hat{\beta}_e^{*(\tau)}$ in $\hat{\Delta}_S^{q_\tau}$ is called the reweighting error as it shows how well the reweighted distribution of characteristics in year *e* mimics the distribution in year b. If $\hat{\Psi}^e(X)$ was estimated consistently, this term tends to be close to zero in large samples.

Since the focus of this paper is the effect of foreign ownership, I am interested in the contribution of the foreign ownership dummy in X to the total composition and wage structure effects. Because of the additive separability assumption, the contributions of single covariates can be partialed out easily just like in the case of the OB decomposition. The pure composition effect in (27) can be decomposed in detail into

(29) $$(\bar{X}_e - \bar{X}_e^*)\hat{\beta}_e^{(\tau)} = \left(\bar{f}_e - \bar{f}_e^*\right)\hat{\beta}_{1,e}^{(\tau)} + \sum_{i=2}^{k}\left(\bar{Z}_{i,e} - \bar{Z}_{i,e}^*\right)\hat{\beta}_{i,e}^{(\tau)},$$

and the pure wage structure effect in (26) into

(30) $$\bar{X}_b\left(\hat{\beta}_e^{*(\tau)} - \hat{\beta}_b^{(\tau)}\right) = \left(\hat{\beta}_{0,e}^{*(\tau)} - \hat{\beta}_{0,b}^{(\tau)}\right) + \bar{f}_b\left(\hat{\beta}_{1,e}^{*(\tau)} - \hat{\beta}_{1,b}^{(\tau)}\right) +$$
$$+ \sum_{i=2}^{k}\bar{Z}_{i,b}\left(\hat{\beta}_{i,e}^{*(\tau)} - \hat{\beta}_{i,b}^{(\tau)}\right).$$

$\left(\hat{\beta}_{0,e}^{*(\tau)} - \hat{\beta}_{0,b}^{(\tau)}\right)$ represents the wage structure effect for the omitted group, the terms involving elements of $\bar{Z}$ capture the contributions of individual characteristics other than ownership, while the two contributions of main interest are $\left(\bar{f}_e - \bar{f}_e^*\right)\hat{\beta}_{1,e}^{(\tau)}$ and $\bar{f}_b\left(\hat{\beta}_{1,e}^{*(\tau)} - \hat{\beta}_{1,b}^{(\tau)}\right)$. The former measures how the change in foreign penetration contributed to the overall change in the value of a particular quantile of the unconditional wage distribution between the end and the base period, while the latter estimates the contribution of changes in the returns to being employed at a foreign-owned company.

3.5. Stylized Facts on Changes in the Wage Distribution

Before turning to the decomposition analysis of FDI and wage inequality, I present some descriptive figures about the evolution of the dispersion of earnings in general. Figure 3.2 follows changes in real wages over time at five selected percentiles of the wage distribution, compared to their 1986 value. Median earnings have declined dramatically right at the beginning of transition, and even though they started to recover in 1992, the stabilization package introduced in 1995 caused wages to fall back to the 1992 level. Lower quantiles were hit more heavily by the shocks of transition and stabilization, with workers at the lowest decile earning in 1997 just 70 percent of what workers at the same decile had earned in 1986. The tide turned in 1997, when real earnings at all points of the distribution started to rise, and have been on the rise basically until the last sample year. However, since the relapse in the early nineties was so radical, 2002 was the first year when median wages reached again their pre-transition level.

Figure 3.2 also provides evidence on the diverging patterns of real wage changes at different points of the distribution – that is, on increasing wage inequality –, a tendency that started in 1992 and has been maintained more or less throughout the whole sample period. The distance between the top and the bottom decile is the largest in 2000, but this seems to be partly a consequence of the strange behavior of wages at the tenth percentile. The surprising increase in the latter from 2000 to 2002 is due to a government intervention that left the real value of the minimum wage in 2002 seventy percent of its value in 2000, and the minimum wage became the tenth percentile of the distribution. The decomposition analysis that follows later refers only to the 1992-2000 period, so those results will not be affected by changes in the minimum wage legislation.

The evolution of wage inequality is easier to follow on Figure 3.3, where dispersion is measured by the variance of log wages. With a short break in 1995, inequality grew substantially and at a fast pace from the end of the socialist regime to 2000, reaching more than 180 percent of its pre-transition level. The huge increase in the minimum wage between 2000 and 2002 also affected the variance, but the upward sloping pattern continued after 2002 for four years. Finally, in the last two years of data, the dispersion decreased, especially in 2008.

Figure 3.3 also reflects differences in the nature of wage dispersion between the beginning and the end of the period by applying a standard variance decomposition to divide total variance into a within-firm and a between-firm component. While during the last years of socialism, inequality was almost completely a within-firm phenomenon, with the introduction of market mechanisms in wage determination, the share of between-firm variation increased to explain close to sixty percent of total variation in wages by the end of the period. Moreover, between-firm variation seems to closely follow the evolution of the overall variance: it is rising when total dispersion is rising, and falling when the spread in the whole distribution is also falling. This suggests that changes in inequality are mostly linked to factors that are correlated with firm-level heterogeneity.

In all what follows, I will focus on the period between 1992 and 2000, and I will consider the market for female and male employees as separate labor markets. In Figure 3.4, I show how the difference between the ninth and the first decile of the log wage distribution evolved for women and men. As represented by the solid line, the log 90-10 differential grew by 30 percent for both genders. The dashed curve right below shows that there is a difference in the location of the wage distributions of workers employed by foreign and domestic firms, since when removing average wages by ownership group, inequality decreases. This difference in the averages is growing over time, more strongly for men than for women. The evolution of sample averages of earnings is represented separately in Figure 3.5 as well. The two bottom curves in Figure 3.4 show that although the foreign wage premium is correlated with individual characteristics, region and industry, it is not completely explained by them. Residual wage inequality within groups of workers defined by education, experience, occupation, region and industry is much lower than total (unconditional) inequality but these factors do not account completely for either the level or for the growth in wage dispersion. When including the foreign dummy into the yearly wage regressions to predict residual wages, residual inequality further decreases, but residual earnings at the 90th percentile are still 2.9 times higher than at the 10th percentile for women (corresponding to a difference of 1.05 log points), and 3.3 times higher for men. The growth in residual inequality from 1992 to 2000 in the all inclusive setup is 21.5 and 22.9 percent, respectively.

Figure 3.6 demonstrates that with the exception of the early years in case of women, not only the mean (see Figure 3.5), but the variance is also larger for foreign-owned employees.[91] This gap, however, does not exhibit a strongly increasing trend similar to the case of the mean for the male distribution, but widens until 1999 for women. As we see, both the mean and the variance are higher for the foreign group, and both of these facts mean that an increase in FDI will result in a wider spread in the overall wage distribution. This may of course not necessarily be a direct effect of FDI itself, but also of some other factors correlated with ownership, but I will partial out the foreign effect in the next section.

Combining the differences in means and variances, it is useful to quantify how the between-group and within-group differences in wages between foreign and domestic workers and the relative share of each group in total employment contribute to the total variation in wages. Table 3.2a decomposes levels of variances at the beginning and at the end of the period, while Table 3.2b decomposes changes in the variance over time with the help of a rough-and-simple within-/between-group variance decomposition, where the groups are defined according to ownership status. The share of between-group variation increased heavily for both genders, partly because the group-level average wages diverged (i.e. the between-group variance increased), and partly because the share of foreign firms grew substantially in total employment. Of course, the main component in both the level and the change of the variance is the within term, which is not surprising when sorting the workforce into just two broad and heterogeneous groups, and without conditioning on any other variable. Again, for the within variance, the increasing share of the higher-variance foreign group is a factor, but not as much as in the case of the between-group term. Considering gender differences, all types of variation grew more strongly for men, and composition effects have

[91] The coefficient of variation, defined as the standard deviation of log wages divided by the mean of log wages, is also higher for workers of foreign firms by 2-5%.

a higher importance for them than for women. For men, the share of foreign employment in 2000 was 6.8 times higher than in 1992, while the same ratio is 6.2 for women, although for the latter group, employees of foreign-owned companies are more numerous in relative terms in both years.

In the next section, I will use more sophisticated decomposition techniques to estimate the ceteris paribus contribution of FDI to changes in the shape of the unconditional wage distribution.

3.6. Decomposition Results

Before presenting the results of a parametric decomposition by quantile, Figures 7, 8a and 8b help to visually inspect how changes in FDI are correlated with changes in the shape of the density of wages, using the non-parametric density decomposition described in Section 4.1. In Figure 3.7, I depicted kernel density estimates of actual wage distributions in 1992 and 2000, and for the counterfactual distribution of a hypothetical state where all characteristics of workers are distributed according to actual shares in 2000, except for ownership that is supposed to be distributed as in 1992; and all returns to individual characteristics are determined by the 2000 wage structure (including returns to foreign ownership). The construction of this counterfactual density followed equation (4) by reweighting the 2000 sample with weights defined in (5). The difference between the counterfactual distribution (marked with the dashed line) and the actual distribution in 2000 shows the effect of the change in FDI penetration between 1992 and 2000, given that the identifying assumptions outlined in Section 4.1 hold. Since the 2000 form of the conditional distribution of wages given the covariates is supposed to prevail, this difference should only capture the effect of the change in the distribution of foreign ownership (i.e. in the share of foreign employment), as opposed to changes in the foreign wage premium.

For both men and women, the changes in factors other than ownership composition increase inequality in the lower end of the distribution, while they do not seem to alter much the shape of the density in the upper end. In contrast, the increase in FDI shifts the location of most of the quantiles to the right, with the exception of very low wages. Besides the location shift, we can observe an increase in the spread of the distribution, especially in case of male earnings.

Figures 8a and 8b display the wage structure effects of foreign ownership. As discussed in Section 4.1, isolating this effect on the density is trickier, and one has to construct the necessary counterfactual distributions separately for the base and end periods, and the effect of the change in the foreign wage premium is given by a difference-in-differences formula in (10). The counterfactual distribution in this case is one where the sample of workers of domestic companies is reweighted in each year to simulate a state where no workers are employed by foreign-owned firms, and the distribution of characteristics in the whole sample is represented by the reweighted subsample of domestic firms. We see in Figure 3.8a that foreign ownership basically has no effect in the base year through a different pay scheme on the density of wages. This is not surprising of course, given that the fraction of foreign-owned enterprises was anyway very small in 1992. In 2000, the picture changes slightly – more so for women than for men – since higher wages paid by foreign employers shift the unconditional earnings distribution to the right. For men, this seems to be a pure location shift – with the exception of the bottommost percentiles – but for women, it also results in a higher kurtosis of the density. Taken all density graphs together, we can conclude that the composition effect of FDI on the shape of the wage distribution was the dominant factor and not the wage structure effect. In what follows, I will estimate these effects parametrically for selected quantiles of the unconditional wage distribution.

The rest of this section builds on the methodological framework introduced in Section 4.2. The steps of estimation are the following. First, I reweighted the sample in year 2000 by an estimated version of the weighting factor defined in (25). The purpose of this was to create the counterfactual distribution for the decomposition in which the distribution of characteristics mimics the distribution in 1992. Second, I estimate for 19 quantiles (for every fifth percentile from the 5^{th} to the 95^{th}) the RIF as defined by (22). Third, I use the estimated RIFs as dependent variables in the unconditional quantile regressions that I run for every quantile separately, and where the regressors are foreign ownership and other covariates including education, potential experience, occupation, region and industry. The regressions are estimated by OLS clustering for firm-level heteroskedasticity. Finally, I decompose changes in RIFs (basically changes in unconditional quantiles) with the standard Oaxaca-Blinder technique, but within the framework outlined in (26)-(30).

The estimated coefficients from the unconditional quantile regressions are presented in Figure 3.9a through Figure 3.10c, separately by gender (Figure 3.9 – men, Figure 3.10 – women) for the base year (gray lines and markers) and for the end year (black lines and markers). The coefficients are plotted against quantiles for each group of covariates. Remember from Section 4.2 that every coefficient measures the estimated effect of increasing the share of workers in the population with the given characteristic on the given quantile of the unconditional wage distribution, holding everything else constant. For example, the plot for university (and college) graduates in Figure 3.9a tells us that in 2000, a ten-percentage-point increase in the number of male workers with completed higher education would shift the 90th percentile of the unconditional wage distribution of men to the right by 16.5 percent (0.1*1.615), while the median by only 4 percent (0.1*0.404), ceteris paribus. It follows that positively sloped curves are evidence of a potentially inequality enhancing covariate, while characteristics with decreasing curves might attenuate wage inequality, if their relative importance increases in the population.

Although it would be instructive to spend time with the in-depth discussion of other covariates, since the focus of this paper is foreign ownership, I will concentrate on the foreign effect. Consider first the case of men in Figure 3.9a. In 1992, the effect of a location shift in the share of foreign workers is clearly estimated to be dispersion enhancing. Nonetheless, the foreign effect is positive at all quantiles, so that higher FDI inflow has a wage increasing impact not only on average, but at every point of the distribution. Note, however, that this does not mean that all workers – including those of domestic firms – necessarily benefit since one of the crucial assumptions of the RIF regression framework is the invariance of the conditional wage distribution to underlying changes in covariates, which effectively means that spillover effects of FDI are assumed to be zero. By 2000, the effects below the median get roughly equalized with the exception of the lowest quantile, but that coefficient is probably estimated with noise as apparent from the other plots as well. Above the median, the inequality enhancing effect remains about the same as it was in 1992.

For women, the pattern is more interesting, displaying a double U-shape. The relationship between the unconditional wage effect and the position in the distribution is concave in the bottom part of the distribution, while it is convex in the top part, with the inflection point being somewhere around the sixth decile in 1992 and around the median in 2000. In other words, a ceteris paribus growth in the share of female workers employed by foreign firms has an inequality increasing impact on very low and very high earnings, while an inequality mitigating impact on medium earnings. Also, the wage effects are estimated to be higher in 2000 than in 1992 for the low and the high end, but lower for the middle section of the distribution. Moreover, the largest effects are close to the median worker in 1992, and even in 2000, the effects close to the second to third deciles are as high as for the top two quantiles, which tells a completely different story from the case of men.

The estimated effects discussed so far only reflect a snapshot in time, but do not help per se in quantifying how actual changes in the distribution of covariates affected actual changes in the unconditional distribution of wages over time. It is useful to refer to a remark by Fortin, Lemieux and Firpo (2011) who point out the importance of decomposition exercises by drawing attention to the fact that although numerous studies find the returns to education to be large (and significant), the differences in human capital endowment over time or across countries only account for a small part of either the growth in GDP over time or of GDP differences between countries. Thus, estimating large positive wage effects of foreign ownership at any point in time does not necessarily mean that a more pronounced presence of foreign investors in the Hungarian business sector had a large influence on the wage distribution. How large it was can be answered by the detailed decomposition of quantile influence functions.

Prior to the analysis of FDI's contribution to wage changes, I summarize the results of the aggregate decomposition according to (26)-(28) in Figure 3.11. Actual changes in wages by quantile follow an increasing function, indicating a rise in inequality across the distribution. The curves are very similar for the two genders, with the male plot being somewhat steeper in the middle. The two error terms – $\left(\hat{\beta}_e^{(\tau)} - \hat{\beta}_e^{*(\tau)}\right)\bar{X}_e^*$ and $(\bar{X}_b - \bar{X}_e^*)\hat{\beta}_e^{*(\tau)}$ in (27) and (28), respectively – both lie very close to the zero line. The first one – representing specification or approximation error – being small means that, first, the bias arising from the linear specification of the conditional expectation of the RIF is small, and second, that although the RIF projection is a local approximation it is doing a good job in measuring the effect of larger changes in underlying characteristics.[92] The negligible magnitude of the second error term is evidence of the reweighted (counterfactual) distribution of covariates in 2000 being in fact close to the actual distribution of 1992, which is what we wanted.

By inspecting curves for the composition and wage structure components in Figure 3.11, we see that the positive real wage changes across the distribution are mostly driven by composition effects, while wage structure effects are mostly responsible for the wider spread of the distribution by the end of the period, for both genders. Changes in the composition of the workforce do also have some inequality boosting impact, especially at the two ends of the distribution, but it is rather a location shift type of effect that dominates. Changes in the returns to skill and other characteristics affected negatively quantiles below the median, while benefitted the upper half. For the lowest ten percent of the distribution it was enough to offset the positive effects of composition changes so that wages at these quantiles decreased from 1992 to 2000.

Let us now move to the detailed decomposition by covariates as described in equations (29) and (30) for each quantile with rank τ. Figure 3.12 depicts the total contributions of each covariate (or group of covariates) to the decomposition, by adding up composition and wage structure effects for each. The "Other" plot merges the error terms from Figure 3.11 and the wage structure effect for the omitted group in the regressions, that is, the term $\left(\hat{\beta}_{0,e}^{*(\tau)} - \hat{\beta}_{0,b}^{(\tau)}\right)$ from equation (30). We see that foreign ownership is a major factor in wage changes over time for every quantile and for both genders. On average across quantiles, 0.085 log points are explained by the increase in FDI of the

[92] Note that we might have expected the specification error to be small due to the fully flexible specification of the RIF regressions by dummying out educational, regional, industrial and experience categories.

changes in male wages. This is quite substantial considering that wages changed by 0.143 log points on average. For women, the same numbers are 0.090 against a total change of 0.153. Turning to the by-quantile effects, the contribution of FDI to wage changes is mostly uniform across the male distribution, especially between the second and sixth deciles. Foreign ownership only has an inequality enhancing effect in the top forty percent of the distribution. Concerning female earnings, the pattern reminds us of the pattern of estimated coefficients from yearly regressions in Figure 3.10a. We observe the double U-shaped curve, only in a much flatter version. Regarding other characteristics, education and industry had strong inequality increasing effects between 1992 and 2000 for both genders, while regional changes decreased dispersion. Occupational changes have a large and inequality mitigating effect for men, and are less important, and have a mixed effect on inequality for women.

Finally, I divide the total contributions of characteristics to effects due to changes in the distribution of the characteristic and due to changes in the returns to the characteristic. I will only consider the "pure" composition and wage structure effects and not deal with the specification and reweighting errors as these were shown to be plausibly negligible. Figures 13a and 13b clearly demonstrate that the dominant factor in the contribution of foreign ownership to wage changes is the increase in the share of employees working for foreign firms as wage structure effects are very close to zero for both men and women. Within composition effects, FDI is the leading explanation across the whole wage distribution. Since wage effects are negligible, the heterogeneity of the foreign composition effect by quantiles takes on the same shape as the total foreign effect in Figure 3.12. For men, the main impact of the rise in the prevalence of foreign companies was a location shift of the distribution, with extra wage premia above the median, increasing in the rank in the distribution. However, because the curve of total wage changes for the upper quantiles is even steeper, the relative explanatory power of foreign ownership decreases when moving towards higher earnings, as other factors' importance – especially that of education – gets higher.

The total change in the log 90-10 wage differential was 0.376 between 1992 and 2000 for men, and the implied contribution of foreign composition effects is only 0.020 log points (computed as the difference between the composition effects estimated on the ninth and the first deciles), that is, about five percent of the total change. For the 90-50 differential, it is 0.187 versus 0.034, while for the 50-10 it is 0.189 versus -0.013 log points.[93] This means that for the lower half of the distribution, FDI even had an attenuating effect on growing inequality. For comparison, note that changes in the skill composition of the workforce, as measured by highest degree of education, contributed by 0.040 log points to the total change in the 90-10 differential, while by 0.028 log points to the change in the 90-50 differential. Note also that composition changes related to labor market experience, regions and occupations had only a minuscule impact on changes in unconditional wages.

For women, the major factors regarding composition effects in the upper graph of Figure 3.13b are foreign ownership share, education, industry and occupation, with the first being by far the most important. The foreign effect varies more by quantile than in case of men, displaying an inequality decreasing pattern in the major middle part of the wage distribution, increasing dispersion only at the low and high ends. It follows that of the total changes in the 90-10, 90-50 and 50-10 inequality measures of 0.349, 0.170 and 0.180 log points, changes in foreign penetration account for a mere 0.010, 0.018 and -0.008 log points, respectively.

The estimated wage structure effects are harder to interpret as they depend on the choice of the omitted group. Firpo, Lemieux and Fortin (2011) discuss the issue in detail and survey possible solutions from the literature. The omitted group problem, however, does not affect binary variables, so the estimated coefficients on the foreign dummy would not change, if I specified another base group. As we saw, the contribution of FDI to overall wage changes by quantile through changes in the foreign wage premia is rather small. Wage structure effects of all other covariates have to be taken with care.

[93] See Appendix Table 3.

3.7. Conclusions

The novelty of this research was to examine the relationship between foreign direct investment and changes in the unconditional distribution of wages using a new method that enables the detailed decomposition of wage changes by quantiles on a sample of workers in the Hungarian business sector. Hungary experienced both a huge amount of FDI inflow during the nineties and significant changes in the location and the shape of the earnings distribution, so it provides an excellent subject of analysis regarding the effects of foreign ownership. A further advantage was insured by linked employer-employee data that facilitated the exact measurement of ownership status and the inclusion of several worker characteristics to the analysis as controls.

I found that wage inequality has been on a rising path throughout the 1989-2008 period, with some breaks that however do not affect the subject period of the main focus of investigation, that is the years between 1992 and 2000 when the largest increase in wage dispersion and the largest growth in the share of foreign employment happened. For this latter interval of time, inequality rose by thirty percent for men and for women, as measured by the log 90-10 wage differential. At the same time, the share of workers employed by foreign-owned firms increased from five to close to forty percent.

A non-parametric decomposition of the change in the density of unconditional wages between 1992 and 2000 shows that it was mainly the change in the composition of workforce by ownership status and not a change in returns to ownership status through which FDI affected the wage distribution. Also, this effect was rather a shift in the location of the distribution and less of a change in the shape of the density function. Going beyond the visual inspection of densities, I applied the parametric method developed by Firpo, Fortin and Lemieux (2007, 2009) that builds on the recentered influence function to (i) estimate the effect of the prevalence of worker characteristics on distributional statistics, and to (ii) decompose changes at various points of the unconditional wage distribution into composition and wage structure effects of these characteristics, with particular attention to foreign employment status. The effects of an increase in FDI at any point in time are estimated to be large, positive and significant across the distribution for both genders. For men, the pattern of the effects is suggestive of an inequality enhancing impact, while for women, it is amplifying dispersion at the two ends of the distribution, but has an alleviating impact in the middle.

Concerning the contributions of FDI to actual wage changes by quantiles, the rise in the share of employees working for foreign firms had a substantial positive composition effect at every quantile, but the role of changes in foreign wage premia over time is negligible. The dominant effect of the composition change related to ownership is a general increase in wages across the whole distribution, but it also accounts for about twenty percent of the rise in male inequality above the median, while it explains ten percent for women. The growth in FDI had a slight inequality mitigating effect in the lower half of the distribution in case of both genders.

It is important to note that these estimated effects can only be considered as causal effects of FDI if the very stringent identifying assumptions set in the paper are met, which is probably not true. In particular, the method assumes away (i) different mechanisms of participation in the labor market in 1992 and 2000, (ii) self-selection of workers into foreign employment based on unobservable heterogeneity, (iii) foreign investors systematically selecting target firms for acquisitions with characteristics that are correlated with changes in the wage distribution, and (iv) wage spillover effects of FDI on workers' wages employed by domestic firms. These are all relevant concerns that are not addressed directly in the paper. However, I pointed out the importance of FDI and/or of factors correlated with FDI in examining changes in the distribution of unconditional earnings so that the paper moved beyond the typical analysis of the foreign effect on conditional average wages. Integrating solutions to the above listed identification issues is a subject of future research.

3.8. References

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3.9. Tables and Figures

Figure 3.1: Foreign Penetration in the LEED and in the Business Sector

Notes: Only firms with more than 20 employees. Business sector shares are computed from a comprehensive administrative dataset of the Hungarian Tax Authority. Shares in the LEED are based on sums of firm-level and worker-level sample weights.

Figure 3.2: Changes in Selected Quantiles of the Real Log Wage Distribution (1986=100)

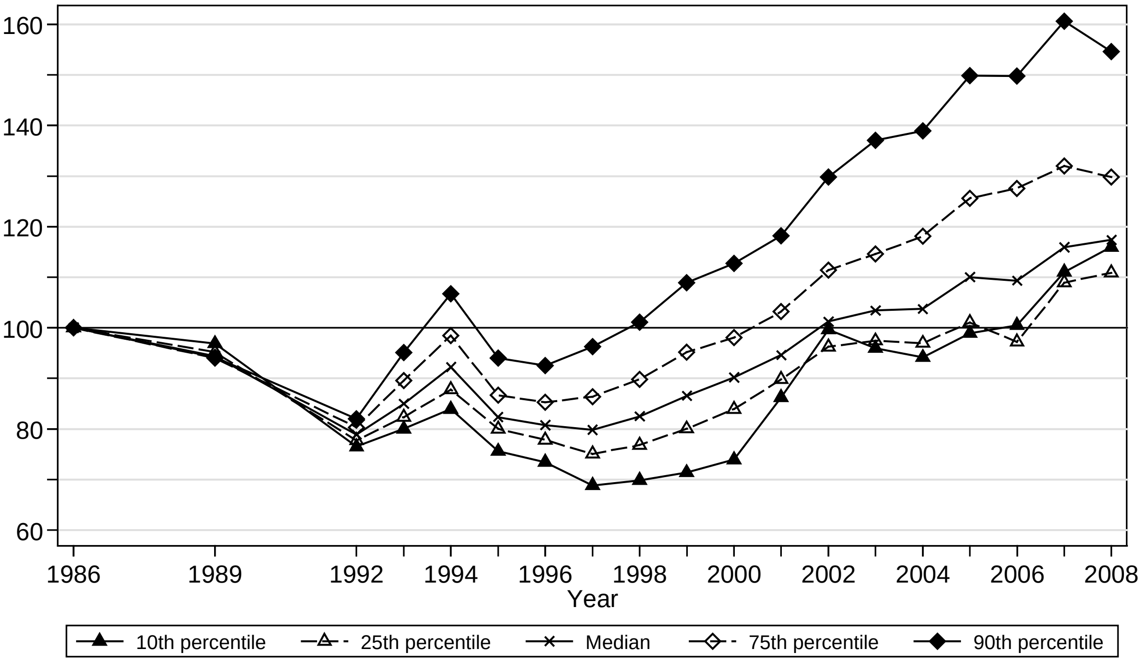
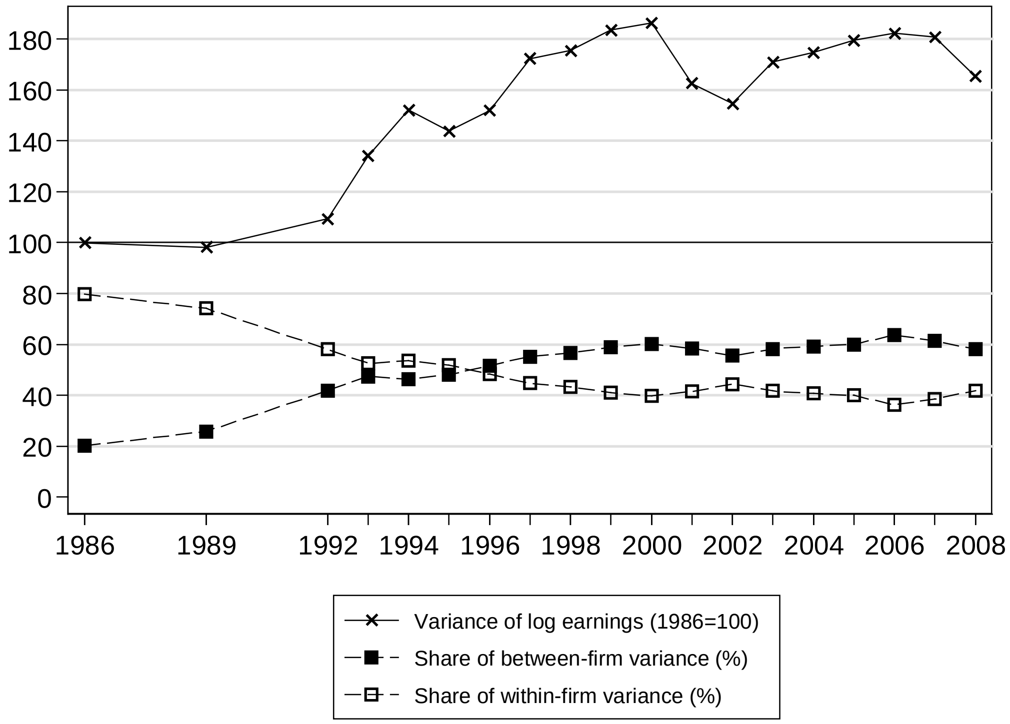
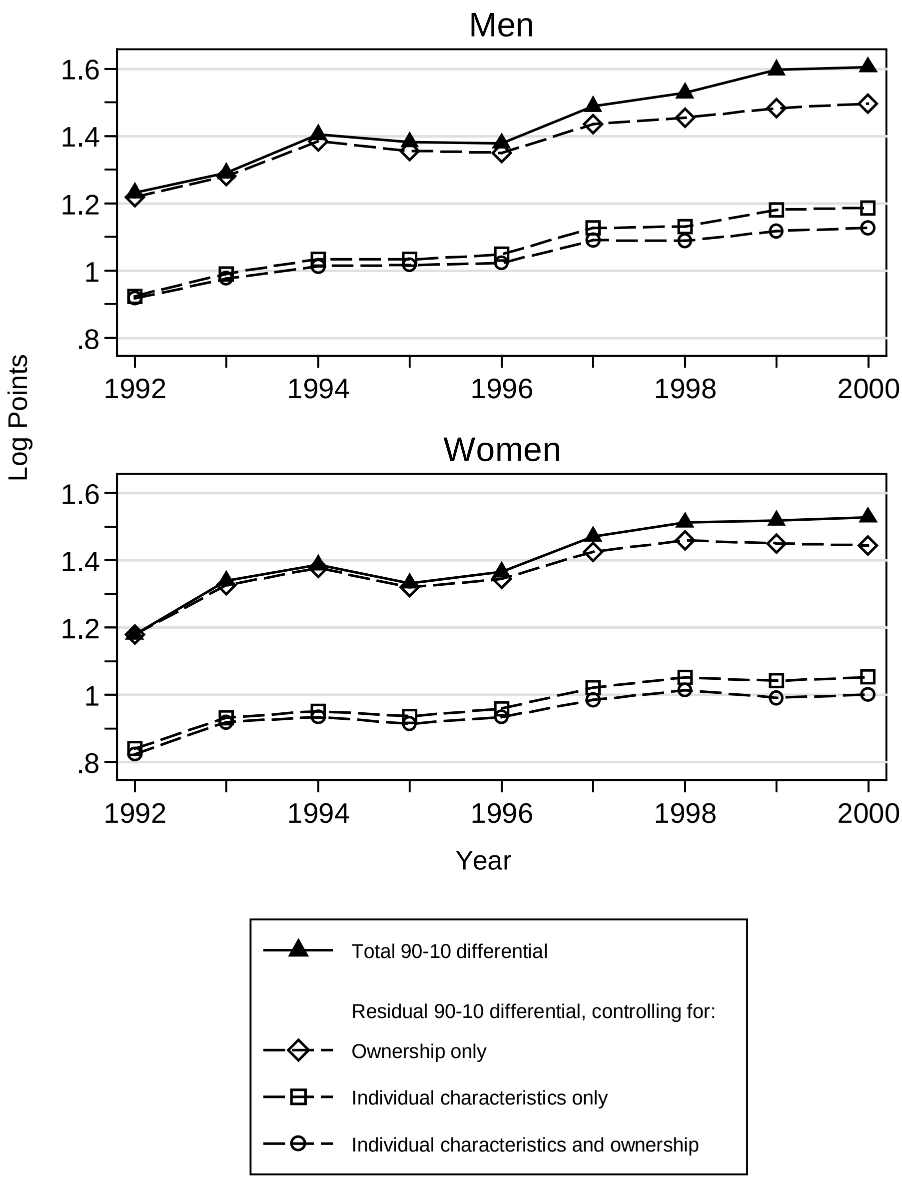


Figure 3.3: Evolution of Total, Between-Firm and Within-Firm Variance of Log Earnings



Notes: Results from a standard within-group/between-group variance decomposition performed by year, where groups of workers are defined as firms, and numbers of employees are used as group (firm) weights.

Figure 3.4: Total and Residual Log 90-10 Wage Differentials



Notes: Residual interdecile differentials computed from the distribution of the residuals of yearly wage regressions. The dependent variable is log monthly earnings, individual controls include highest degree of education, potential experience in levels, potential experience squared and full sets of occupational, industrial and regional dummies. In the "Ownership only" regressions, only a constant and a lagged foreign ownership dummy are included.

Figure 3.5: Evolution of the Mean of Log Earnings by Ownership and Gender

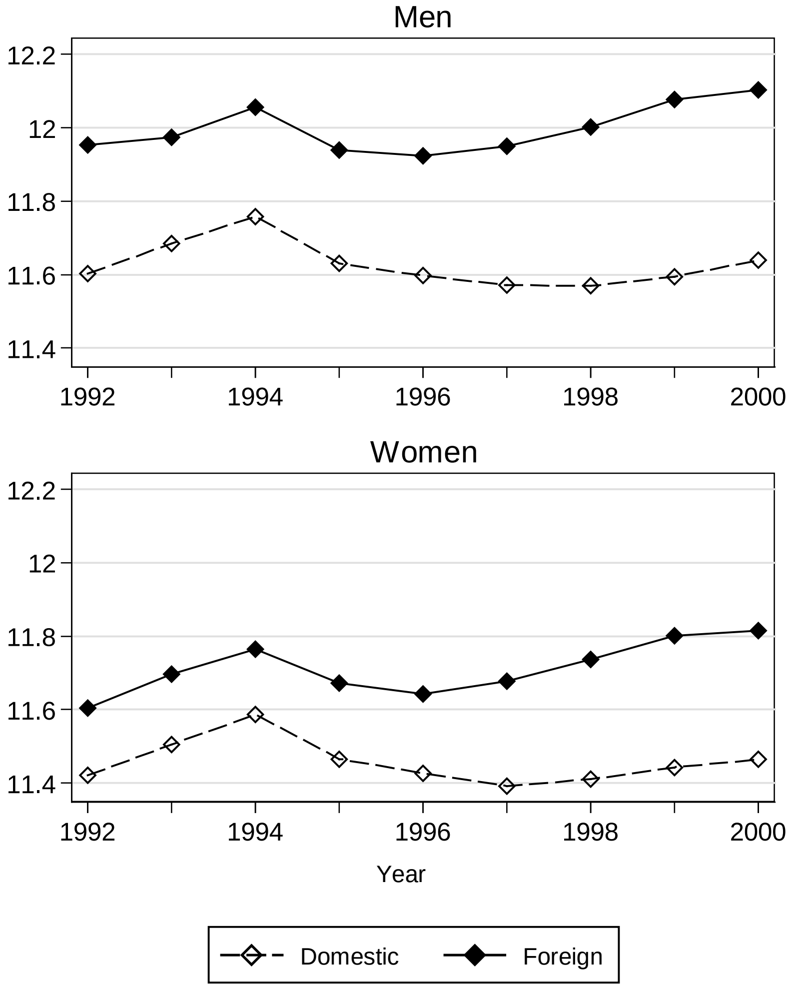


Figure 3.6: Evolution of the Variance of Log Earnings by Ownership and Gender

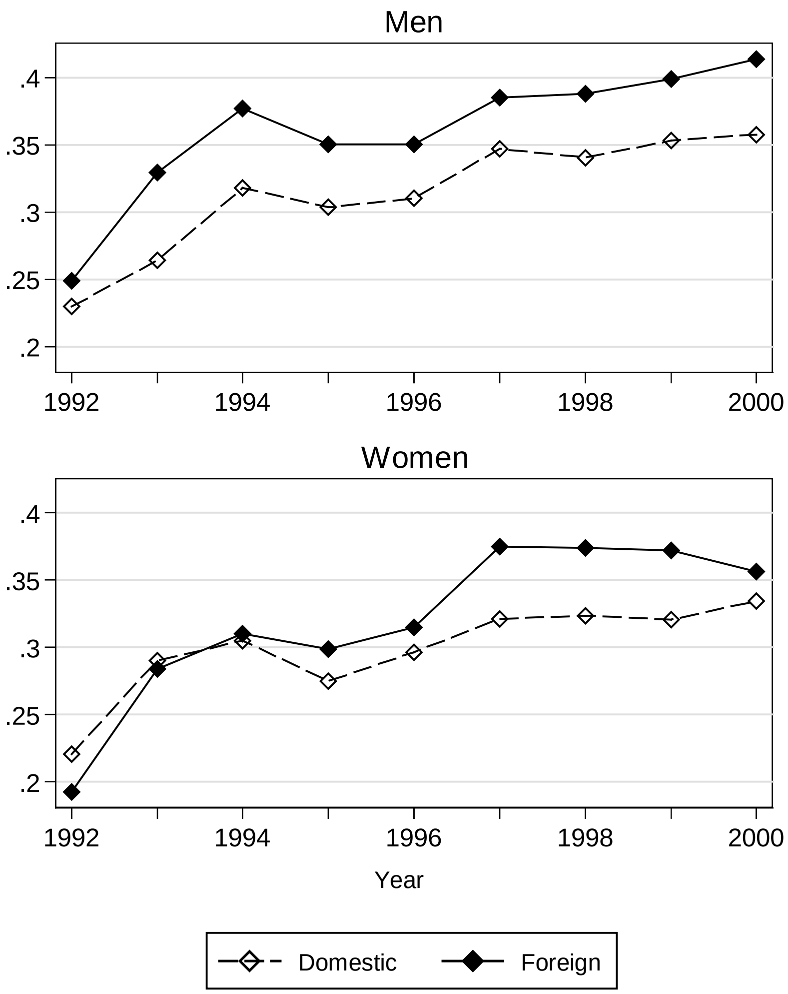
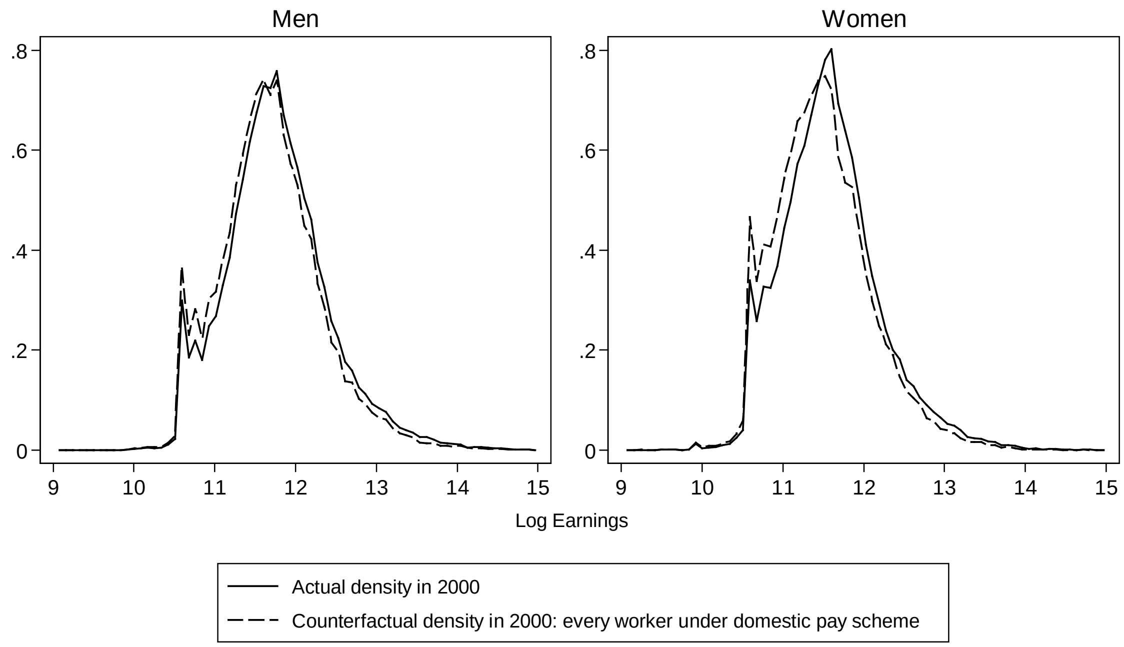


Figure 3.7: Composition Effect of Foreign Ownership on the Density of Log Earnings, 1992-2000

Notes: For the construction of the counterfactual density, the 2000 sample is reweighted to reflect the distribution of ownership in 1992, keeping the distribution of every other worker characteristic unchanged. Weights constructed by the reweighting method of DiNardo, Fortin and Lemieux (1996).

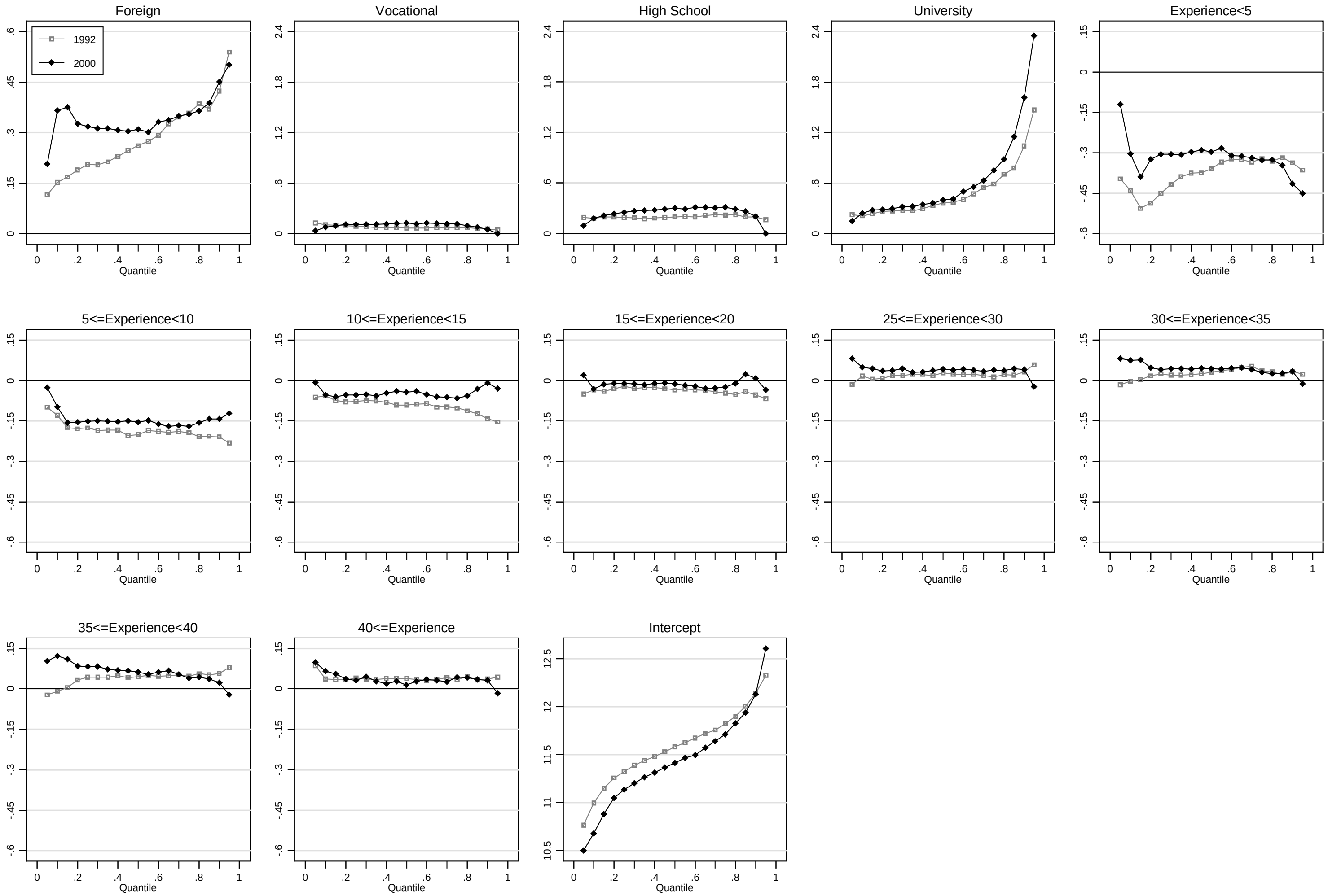
Figure 3.8a: Wage Structure Effect of Foreign Ownership on the Density of Log Earnings, 1992

Figure 3.8b: Wage Structure Effect of Foreign Ownership on the Density of Log Earnings, 2000



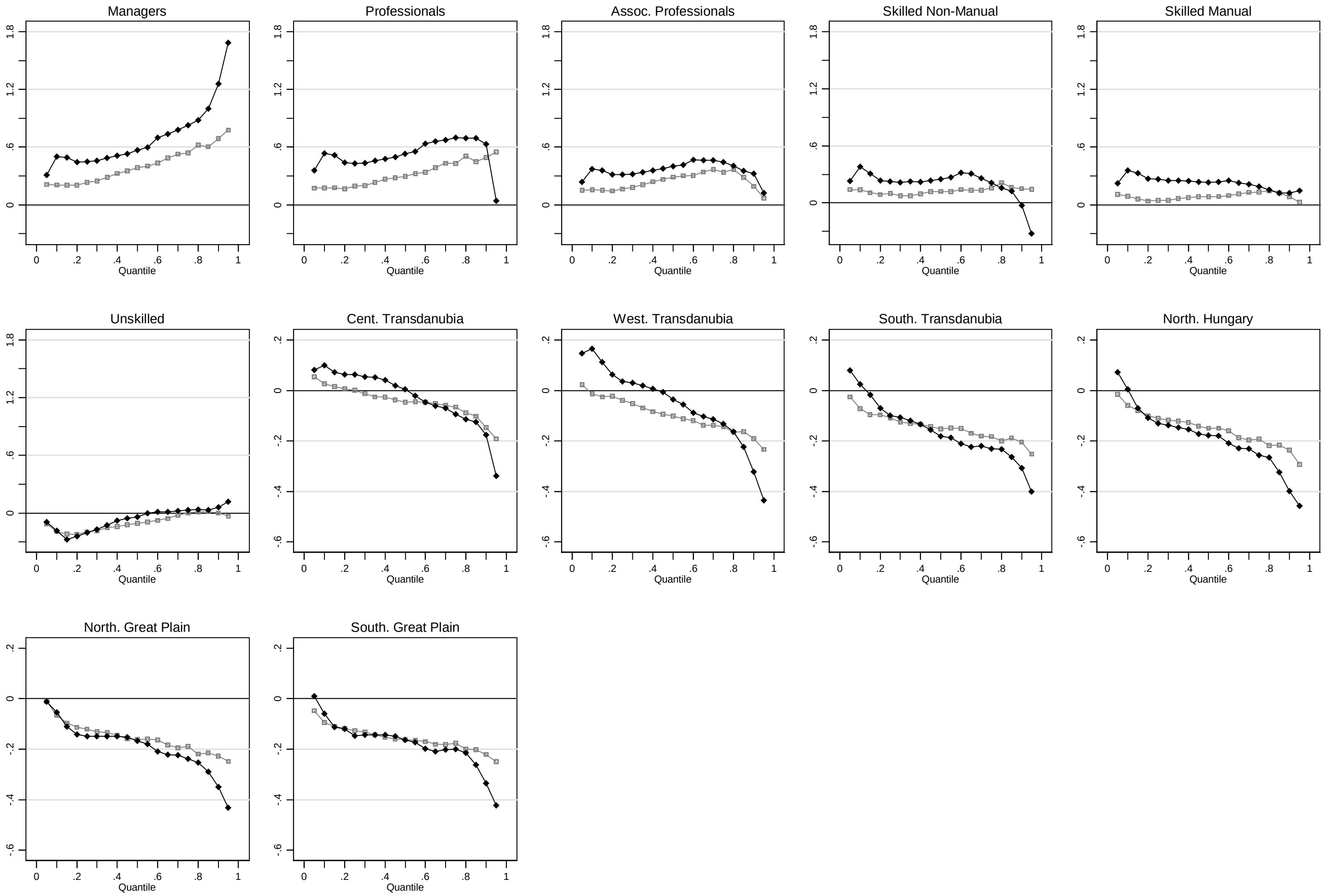
Notes: For the construction of the counterfactual density, the subsample of domestic workers is reweighted in each year to reflect the distribution of the total workforce, using the reweighting method of DiNardo and Lemieux (1997).

Figure 3.9a: Coefficients from Unconditional Quantile Regressions – Men



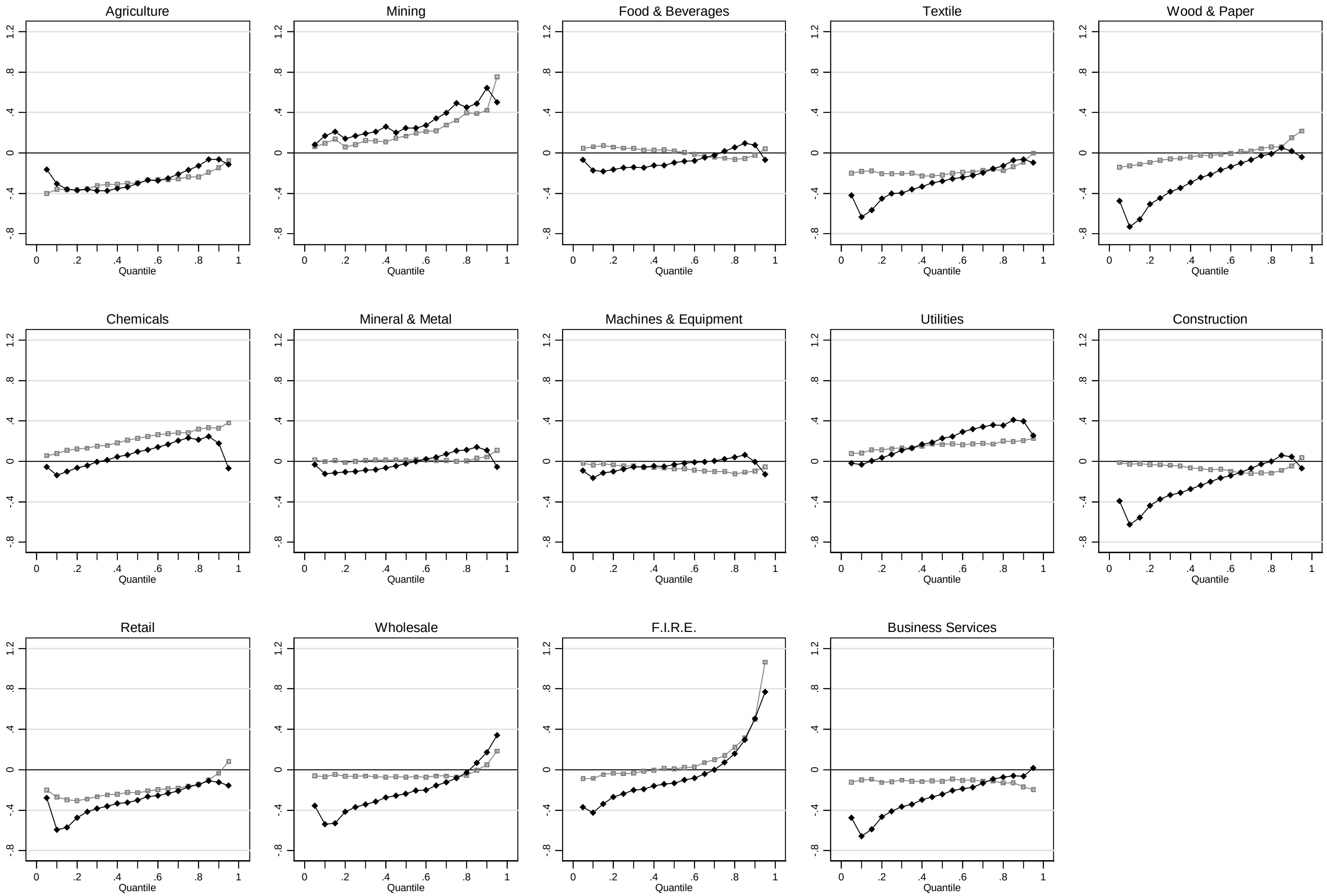
Notes: Omitted group: elementary education, more than 20 and less than 25 years of potential experience, services occupations, Central Hungary, other services industry.

Figure 3.9b: Coefficients from Unconditional Quantile Regressions – Men



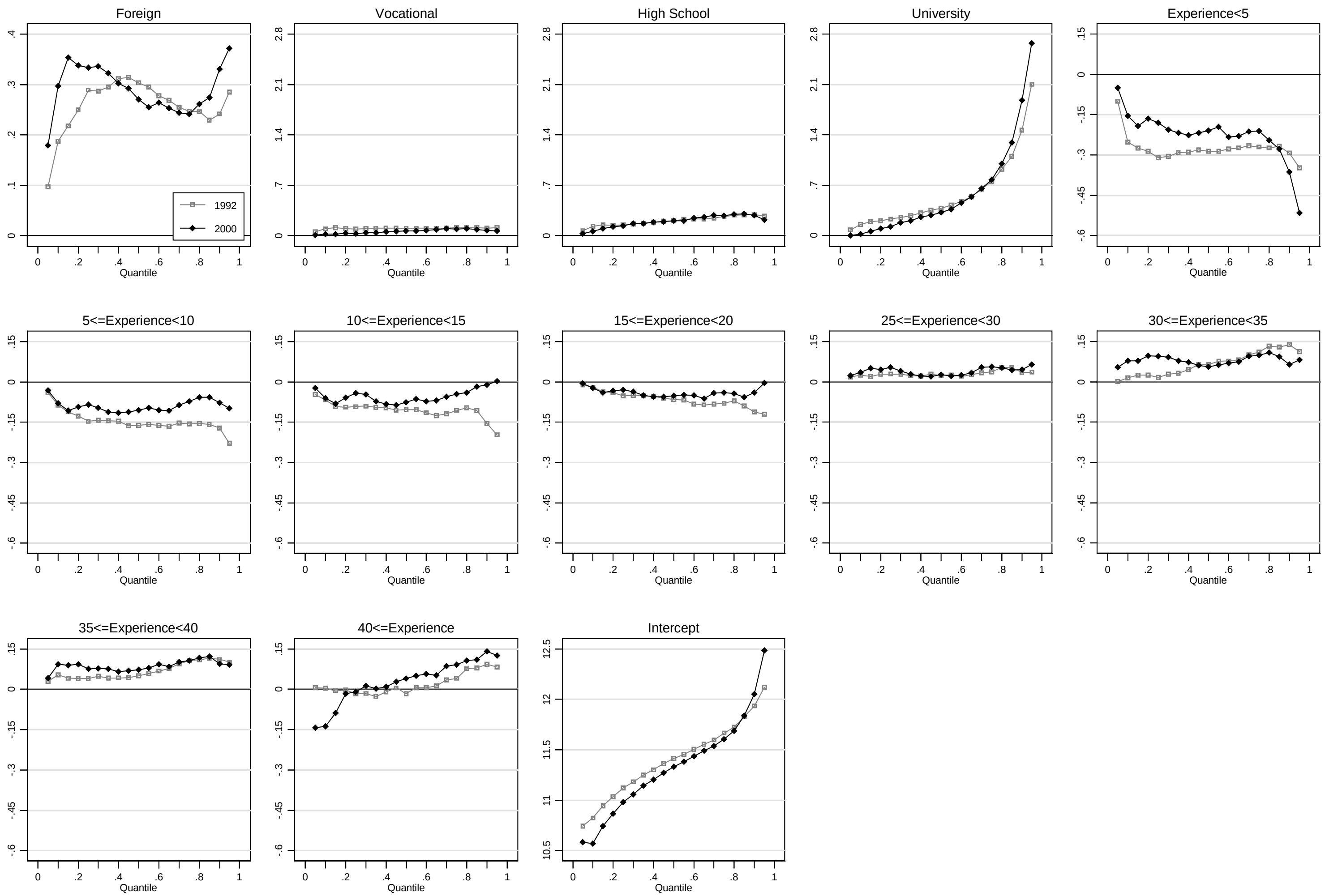
Notes: Omitted group: elementary education, more than 20 and less than 25 years of potential experience, services occupations, Central Hungary, other services industry.

Figure 3.9c: Coefficients from Unconditional Quantile Regressions – Men



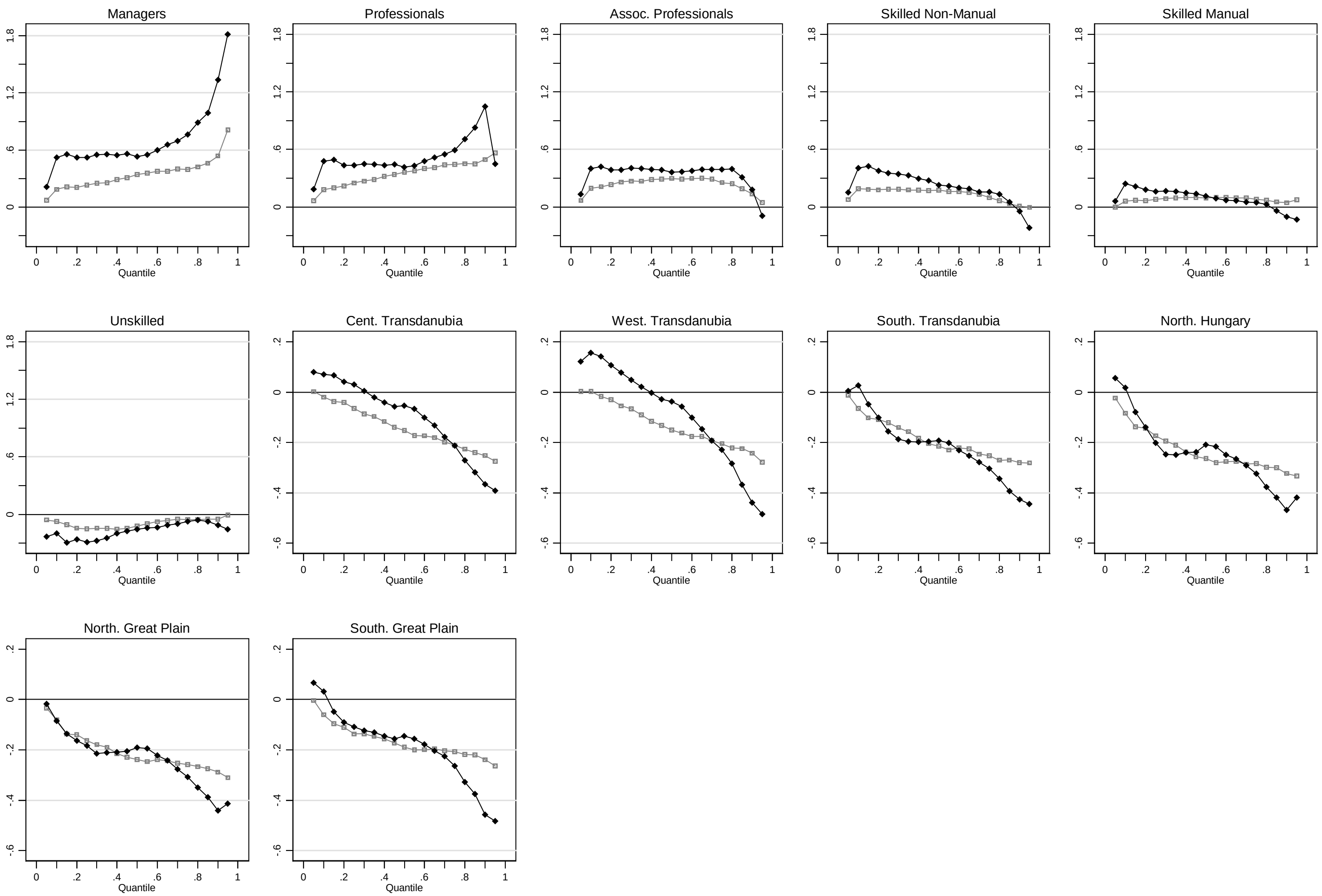
Notes: Omitted group: elementary education, more than 20 and less than 25 years of potential experience, services occupations, Central Hungary, other services industry.

Figure 3.10a: Coefficients from Unconditional Quantile Regressions – Women



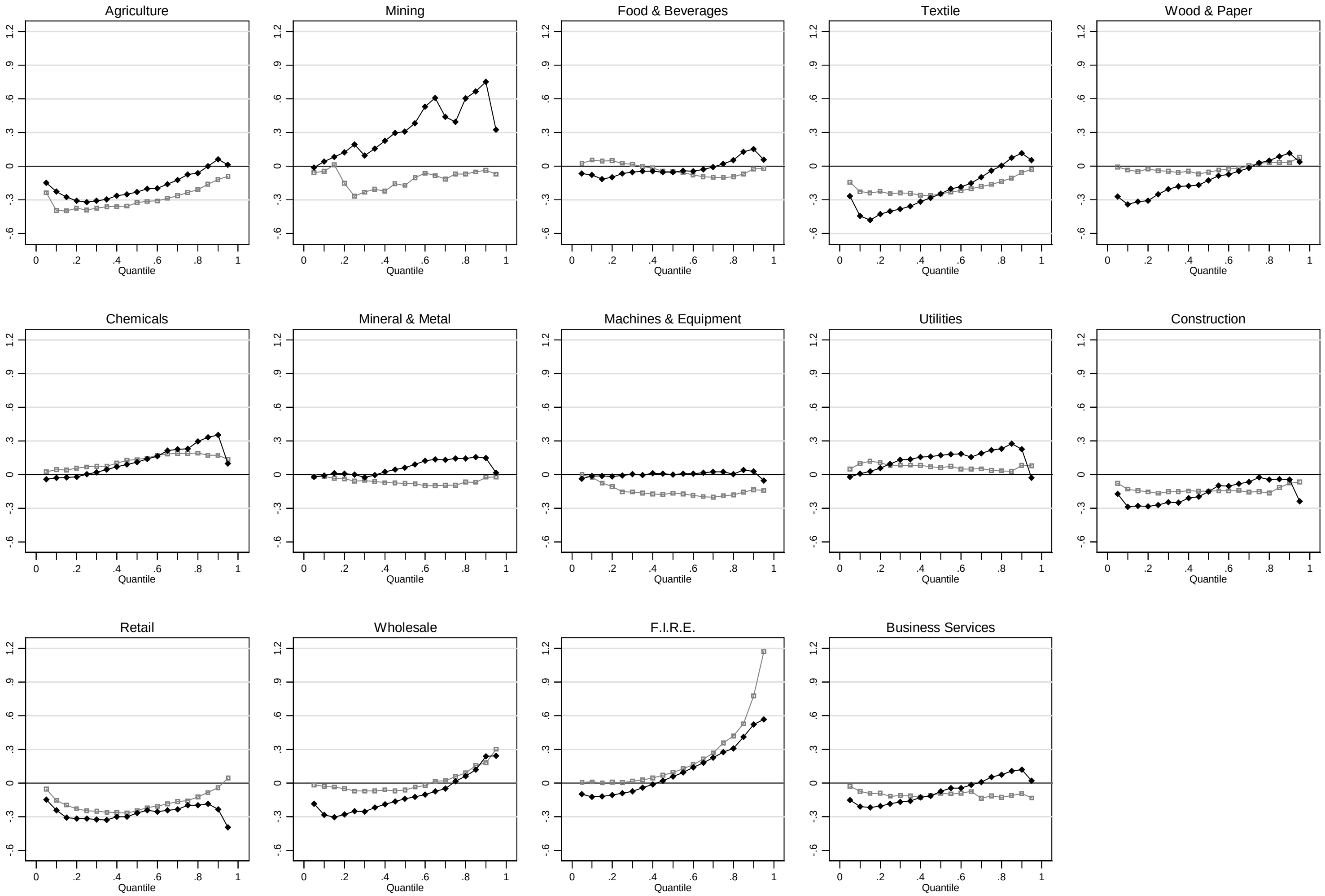
Notes: Omitted group: elementary education, more than 20 and less than 25 years of potential experience, services occupations, Central Hungary, other services industry.

Figure 3.10b: Coefficients from Unconditional Quantile Regressions – Women



Notes: Omitted group: elementary education, more than 20 and less than 25 years of potential experience, services occupations, Central Hungary, other services industry.

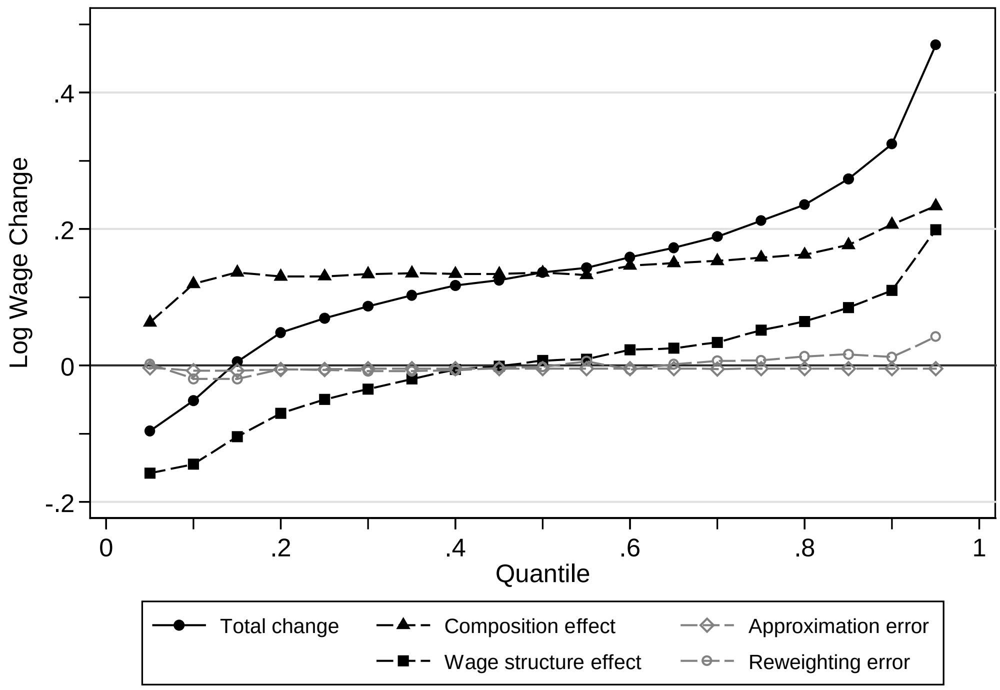
Figure 3.10c: Coefficients from Unconditional Quantile Regressions – Women



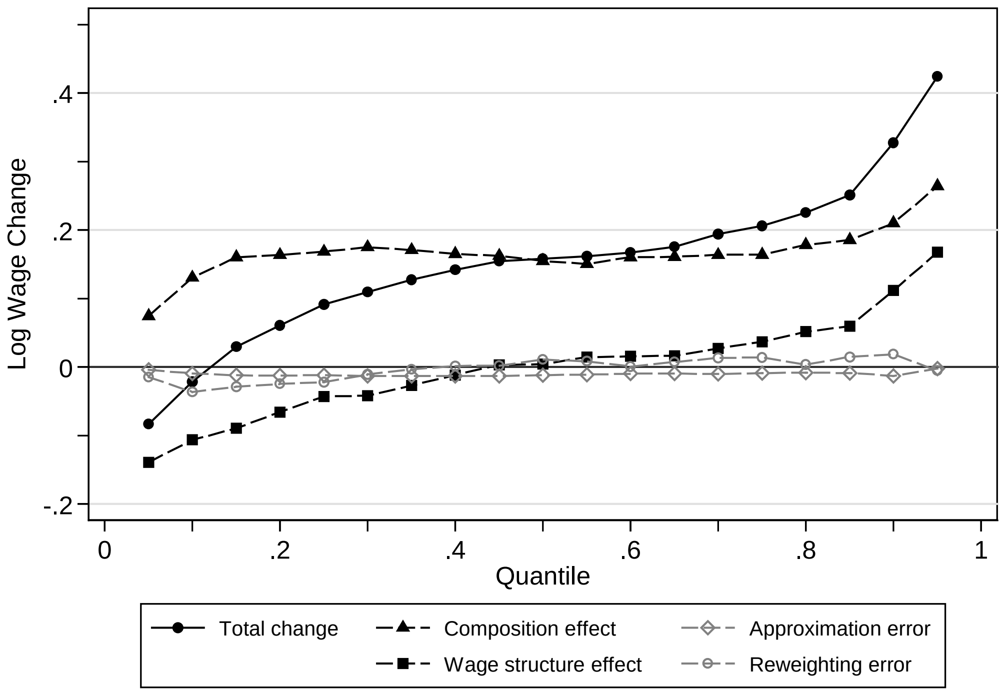
Notes: Omitted group: elementary education, more than 20 and less than 25 years of potential experience, services occupations, Central Hungary, other services industry.

Figure 3.11: Aggregate Decomposition of Total Wage Changes by Quantile (1992-2000)

Men

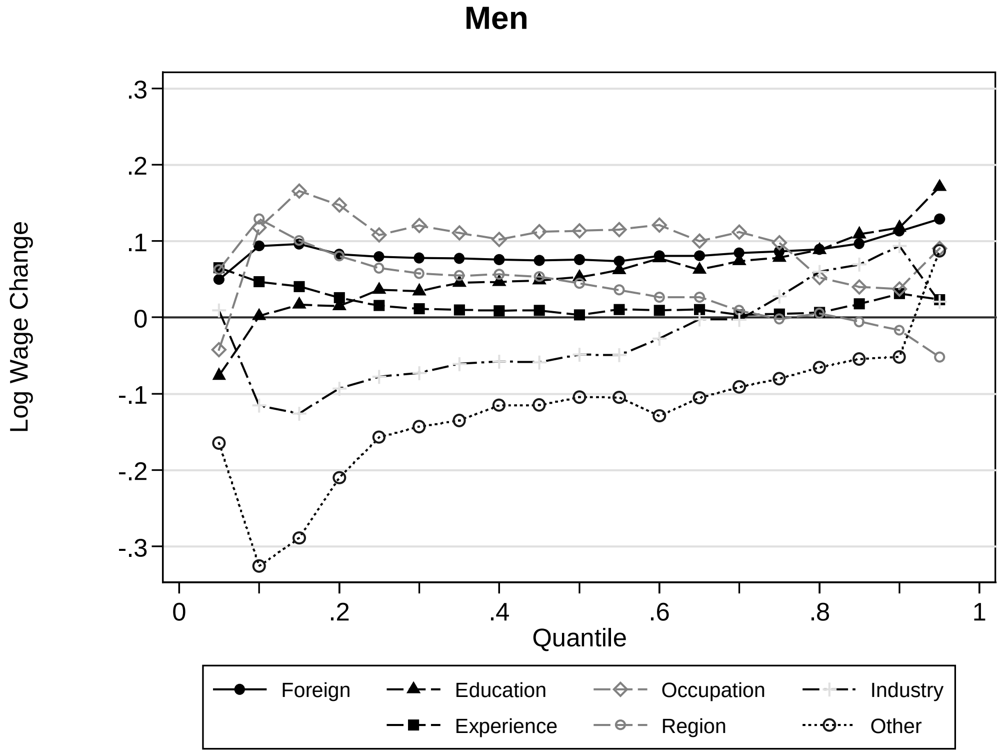


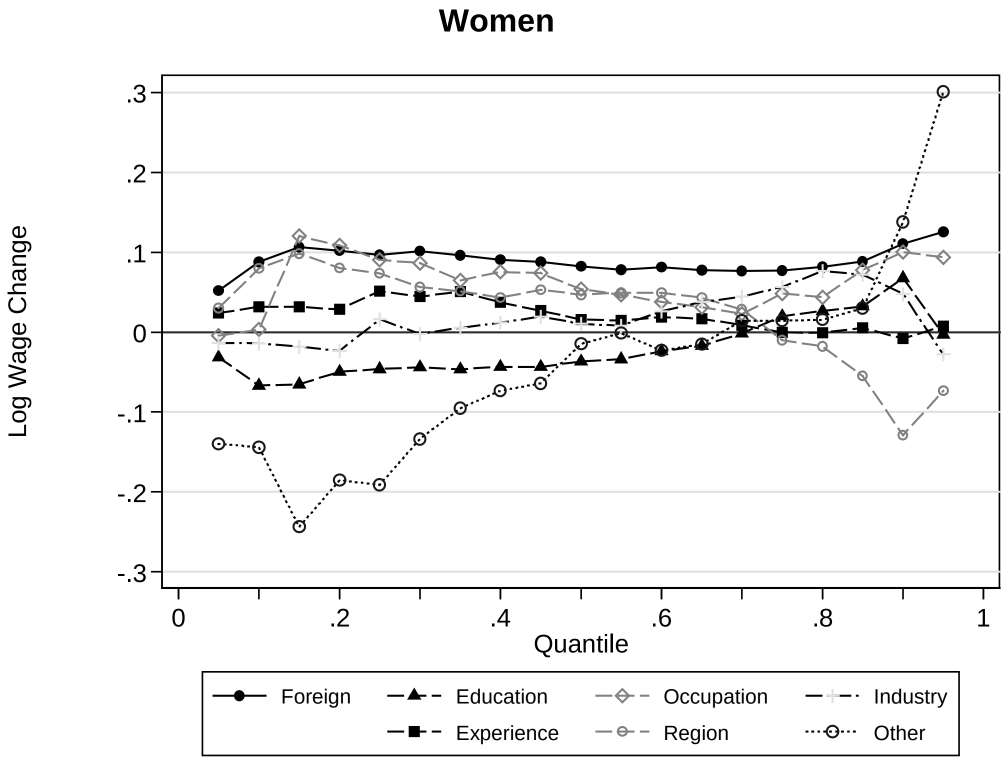
Women



Notes: Based on a reweighted RIF-regression decomposition. Changes measured between 1992 and 2000, and a counterfactual outcome for which the distribution of worker characteristics in 2000 was reweighted to mimic the 1992 distribution.

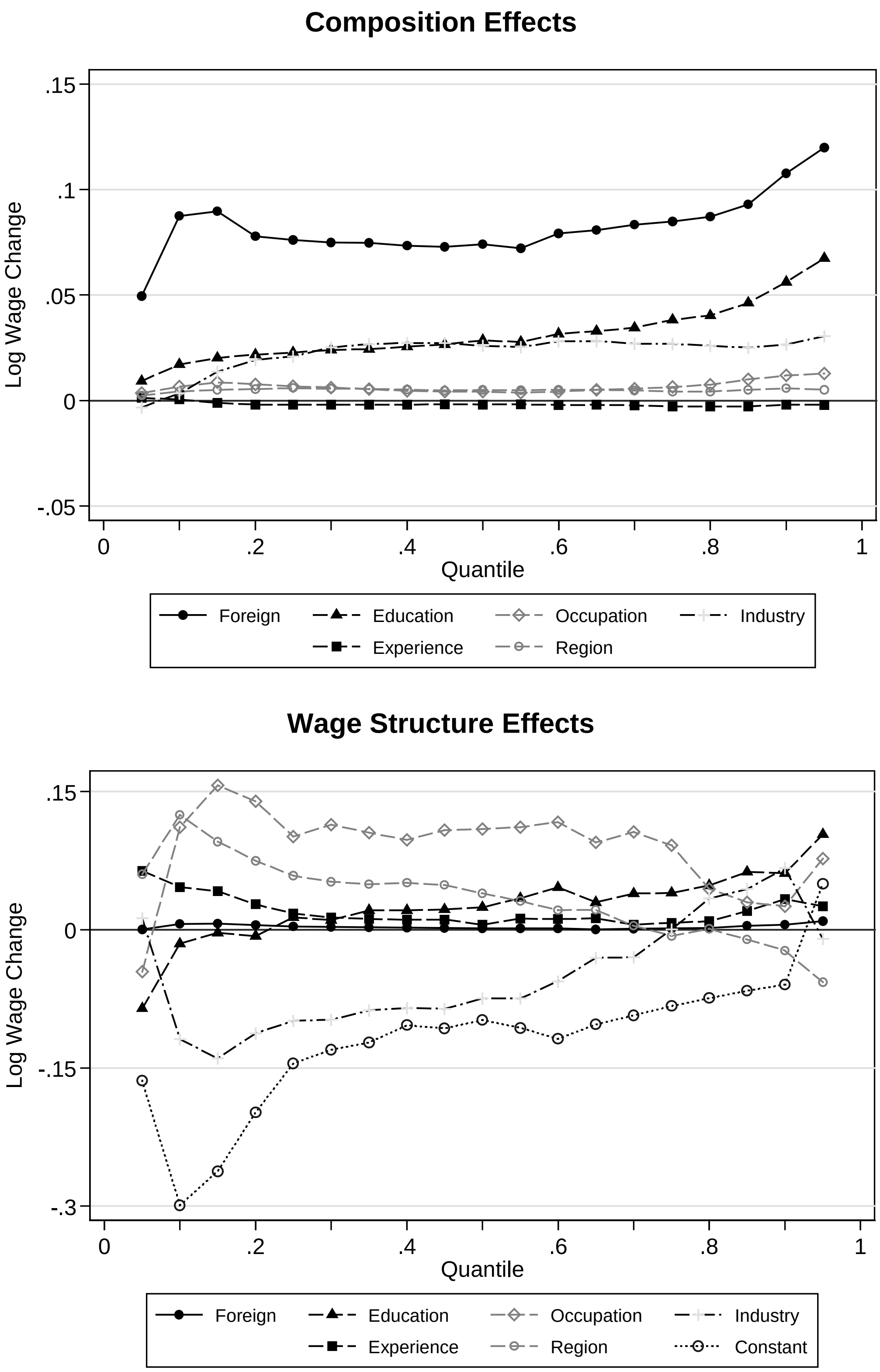
Figure 3.12: Detailed Decomposition: Total Contributions of Worker Characteristics (1992-2000)





Notes: Based on a reweighted RIF-regression decomposition. Changes measured between 1992 and 2000 and a counterfactual outcome, for which the distribution of worker characteristics in 2000 was reweighted to mimic the 1992 distribution. "Other" includes the constant of the wage structure decomposition, and the approximation and specification errors.

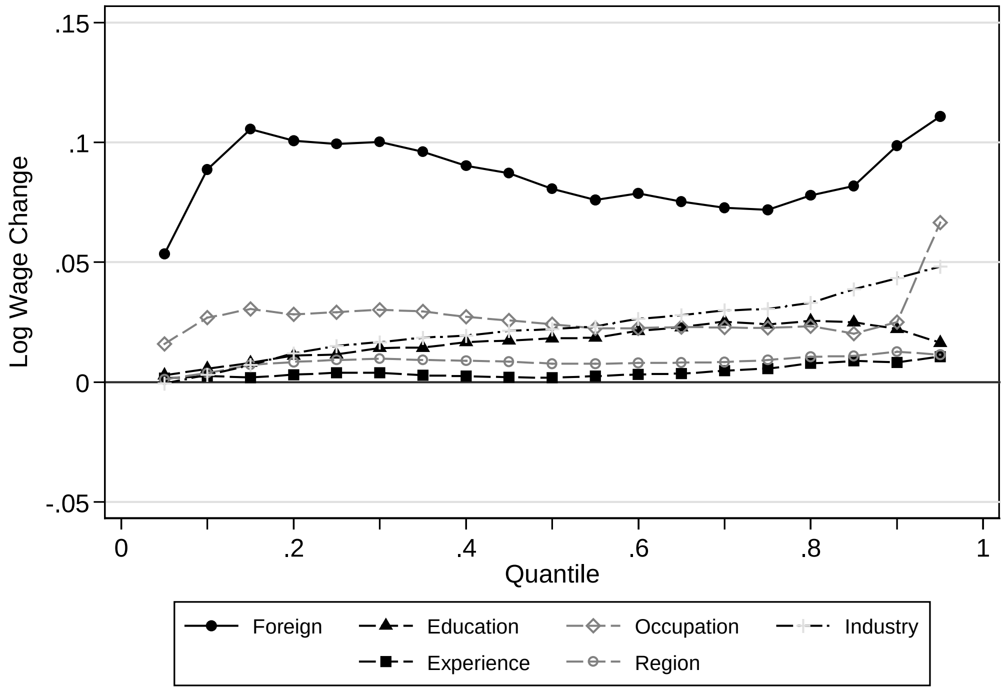
Figure 3.13a: Detailed Composition and Wage Structure Effects – Men (1992-2000)



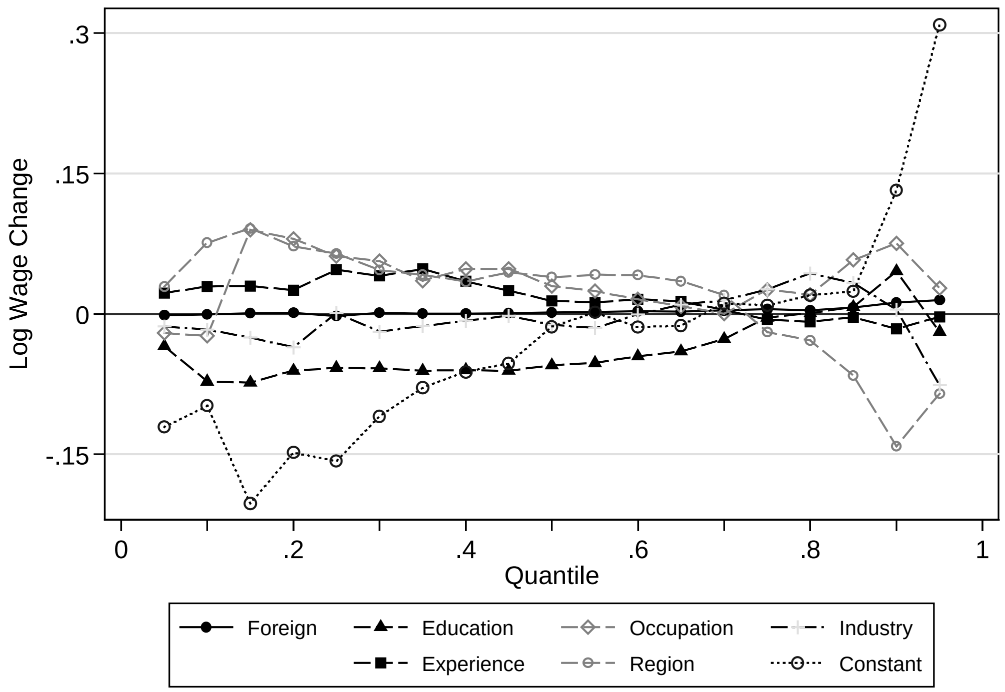
Notes: See Figure 3.11.

Figure 3.13b: Detailed Composition and Wage Structure Effects – Women (1992-2000)

Composition Effects



Wage Structure Effects



Notes: See Figure 3.11.

Table 3.1: Sample Size by Year

	Unweighted	Weighted	
Year	**Worker Observations**	**Employment in the Sample**	**Percent of Total Employment**
1986	523,651	3,205.5	N.A.
1989	355,896	2,389.2	N.A.
1992	78,593	1,705.3	83.1
1993	81,875	1,327.4	74.8
1994	100,641	1,467.1	86.6
1995	102,634	1,482.7	92.1
1996	87,418	1,208.0	76.4
1997	85,451	1,157.6	73.5
1998	86,400	1,178.9	73.2
1999	84,319	1,119.7	70.3
2000	89,919	1,119.8	69.1
2001	86,759	1,109.1	68.6
2002	99,234	1,029.1	65.3
2003	96,143	954.1	61.0
2004	105,808	1,004.6	63.9
2005	113,058	1,033.9	66.7
2006	112,432	1,160.8	73.2
2007	104,788	971.5	62.4
2008	103,893	1,012.2	63.8
Total	2,498,912	N.A.	N.A.

Note: Employment in the Sample (in thousands) = sum of workers employed by firms in the LEED. Percent of Total Employment = sample employment divided by total employment in the dataset of the Hungarian Tax Authority (HTA). Only firms with more than 20 employees included. The HTA dataset contains virtually every double-entry book-keeping company in the business sector, except for years before 1992 when it includes only a sample of firms.

Table 3.2a: Variance of Log Earnings Within- and Between Ownership Groups (Variance Decomposition of Levels)

	Total Variance	Within-Group Variance	Between-Group Variance	Group-Level Variances		Employment Shares	
				Domestic	Foreign	Domestic	Foreign
Men							
1992	0.235	0.230	0.005	0.230	0.249	0.960	0.040
2000	0.415	0.373	0.043	0.358	0.414	0.727	0.273
Women							
1992	0.221	0.219	0.002	0.221	0.193	0.943	0.057
2000	0.370	0.342	0.028	0.335	0.357	0.647	0.353

Notes: Results from a standard within-group/between-group variance decomposition performed by year, where groups of workers are defined as workers of domestic and foreign firms, and numbers of employees are used as group weights.

Table 3.2b: Changes in the Variance of Log Earnings Within- and Between Ownership Groups (Variance Decomposition of Changes)

	Total Change in Variance	Within-Group Change		Between-Group Change		Change in Domestic Variance	Change in Foreign Variance
		Change in Variance	Composition Effect	Change in Variance	Composition Effect		
Men							
1992-2000	0.180	0.129	0.013	0.015	0.023	0.128	0.165
Women							
1992-2000	0.149	0.117	0.007	0.016	0.011	0.114	0.164

Notes: Changes in total variance decomposed according to the decomposition method in Table 3.2a.

3.10. Appendix

Table A3.1: Descriptive Statistics by Ownership Type

	1992		2000	
Foreign Employment Share (%)	4.6		30.5	
	Domestic	Foreign	Domestic	Foreign
Monthly Earnings	116.1	152.4	131.5	202.4
	(71.1)	(104.7)	(134.7)	(225.2)
Female (%)	37.4	46.7	37.0	46.0
Education (%)				
Elementary	32.9	33.8	23.6	19.6
Vocational	32.7	33.5	38.4	33.7
High school	27.1	23.5	29.9	32.7
University	7.3	9.2	8.2	14.0
Experience	22.1	20.4	23.1	19.3
	(10.6)	(10.5)	(10.9)	(10.9)
Occupation (%)				
Elementary Occupations	11.1	10.8	9.6	5.4
Skilled Manual Workers	48.3	58.2	50.5	53.3
Service Workers	9.2	5.0	10.9	7.2
Clerks	6.8	5.4	5.9	6.0
Associate Professionals	12.7	9.6	12.1	14.5
Professionals	6.2	6.9	2.9	6.2
Managers	5.7	4.0	8.2	7.3
Industry (%)				
Agriculture	18.3	0.2	12.3	0.6
Mining	0.2	0.0	0.3	0.0
Food&Beverages	6.2	11.1	6.5	7.6
Textile	5.4	12.3	6.8	9.8
Wood&Paper	2.6	2.6	3.1	2.5
Chemicals	4.8	3.7	2.7	9.5
Minerals&Water	5.3	4.9	6.7	7.5
Machines&Equipment	8.8	43.1	9.8	26.2
Utilities	3.0	0.0	2.8	5.1
Construction	6.1	8.8	6.3	1.8
Retail Trade	9.5	7.2	7.3	7.4
Wholesale Trade	4.0	4.0	4.0	5.2
F.I.R.E.	1.5	0.1	4.5	5.9
Business Services	2.6	1.1	4.9	3.6
Other Services	21.7	0.8	22.0	7.3
N	74,724	3,869	59,987	29,932

Notes: Weighted unconditional means and standard deviations. Earnings measured in thousands of 2008 HUF, deflated by CPI. Female, education, and occupation measured as percentages of total workforce by ownership type. Standard deviations in parentheses. The definition of occupations follows ISCO-88 where Elementary Occupations, Service Workers, Clerks, Associate Professionals, Professionals and Managers coincide with the corresponding major groups; while Skilled Manual Workers cover Skilled agricultural and fishery workers, Craft and related trades workers and Plant and machine operators and assemblers.

Table A3.2: Estimated Coefficients of Foreign Ownership in the Unconditional Quantile Regressions

	Men		Women	
	1992	2000	1992	2000
1st Decile	0.152**	0.366**	0.188**	0.297**
	(0.021)	(0.033)	(0.021)	(0.030)
2nd Decile	0.190**	0.326**	0.250**	0.338**
	(0.023)	(0.022)	(0.029)	(0.028)
3rd Decile	0.204**	0.313**	0.287**	0.336**
	(0.028)	(0.018)	(0.036)	(0.026)
4th Decile	0.229**	0.307**	0.312**	0.303**
	(0.035)	(0.018)	(0.046)	(0.022)
Median	0.262**	0.310**	0.304**	0.271**
	(0.041)	(0.020)	(0.045)	(0.020)
6th Decile	0.292**	0.331**	0.277**	0.264**
	(0.044)	(0.025)	(0.047)	(0.023)
7th Decile	0.347**	0.349**	0.255**	0.244**
	(0.051)	(0.029)	(0.036)	(0.027)
8th Decile	0.386**	0.364**	0.246**	0.261**
	(0.058)	(0.032)	(0.032)	(0.033)
9th Decile	0.424**	0.451**	0.242**	0.331**
	(0.057)	(0.045)	(0.035)	(0.039)
N	44,072	50,495	31,887	37,235

Notes: The table shows coefficients and standard errors from RIF regressions. Other controls include education, experience, region, industry and occupation. ** = significant at 0.01; * = significant at 0.05

Table A3.3: Contributions of FDI to Changes in Log Wage Differentials, 1992-2000

	90-10	90-50	50-10
Men			
Total Change	0.376	0.187	0.189
FDI Composition Effect	0.021	0.034	-0.013
FDI Wage Structure Effect	-0.001	0.003	-0.004
Women			
Total Change	0.350	0.170	0.180
FDI Composition Effect	0.010	0.018	-0.008
FDI Wage Structure Effect	0.013	0.001	0.003

Notes: Computed from the results of RIF decompositions presented in Figures 11-13. Changes measured in log points.