Employment, Wage discrimination & Poverty - EDIPO

Final report

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GENERAL INTRODUCTION

This report summarizes the results and recommendations of a three-year research project EDIPO that brought together economists from the Université libre de Bruxelles (ULB), the Université catholique de Louvain (UCL) and the Katholieke Univeriteit Leuven (KUL). The acronym EDIPO stands for the three encompassing themes of this research: **E**mployment, wage **DI**scrimination and **PO**verty.

The aim of the EDIPO project was to assess the situation of groups among the population known for being confronted to labour-market barriers, which display low employment rates, high unemployment rates and a higher-than-average risk of poverty due to wage inequality. These groups comprise, among others, women (especially aged 50 or more), low-educated inviduals and residents of non-EU origin. More precisely, the objectives ot this project is to assess their situation in terms of i) employability, ii) wage discrimination and iii) relative wages.

While the EDIPO research was grounded on existing research on at-risk groups, its novelty consisted on using matched employer-employee data and a marked focus on firm-level labour productivity. The simultanesous study of three labour market outcomes (employability, age discrimination and relative wages) was made possible by the availability of data on productivity (turnover, value added…), labour costs and wages, for very large samples of firms located in Belgium, mainly active in the private sector, and their employees. Indeed, the bulk of the existing economic research about wage inequality or the sociodemographic groups facing employment barriers has been done by labour economists who use individual-level data (cross-sectional or panel surveys like the EU-LFS, EU-SILC, SHARE, UNECE, administrative sources like the CARREFOUR datawarehouse or the censuses). These data sources provide detailed information about individuals (in terms of their labour market outcomes and their individual/family background, or their productivity-related characteristics: highest degree, labour market experience…). But they suffer from their excessive focus on individuals who represent only the supply side of the labour market, ignoring the role of the demand side: the one of firms. In many works too little is said about the attitute of firms vis-à-vis these groups and its determinants. Robust evidence was missing regarding how these individuals perform inside firms - as a group - and in interaction with other types of workers.

Our research has clearly shown that both the demand side (employers) and the suppply side (employees) need to be considered simultaneously to better understand problematic labour-market outcomes. This allowed us to identify better policy responses to tackle these problems.

The (lack of) employability of at-risk groups using firm-level data

Employability is about having the capability to gain initial employment, maintain employment and obtain new employment if required. Most economists would agree that it is, to a large extent, driven by the ratio of individuals' productivity to their cost to employers. In other words, the willingness of employers to employ/recruit different categories of workers is influenced by their relative average labour cost per unit of output.

We have assessed the willingness of firms based in Belgium to employ at-risk groups and analysed the sensitivity of the productivity-labour costs ratio to the workforce structure of firms, namely the share of women and especially older women (Chapters 3, 4, 5 and 10), the share of low-educated workers (Chapters 6, 7, 8 and 10), the share of part-time and temporary workers (Chapter 5 and 11) or that of groups with non-EU origin (Chapter 9).

The prevalence of discrimination against women, immigrants, part-time and temporary workers in the Belgian private economy

Groups displaying poor labour-market outcomes could be discriminated. Evidence of substantial average earnings' differences between men and women, natives and immigrants, workers with part- and full-time positions and fixed or indefinite work contracts are systematic and persistent outcomes in the labour markets of most developed economies. Commonly, people refer to wage discrimination as the wage differential between members of a minority group (women/immigrant) and the majority group (men/natives), and that manifests itself by a lower pay. Strictly speaking however, from an economic point of view, wage discrimination requires more that wage differences between groups. It implies that equal labour services provided by equally productive workers have a sustained price/wage difference.

The standard empirical approach among economists to the measurement of wage discrimination consists of estimating earning/wage equations and applying Oaxaca (1973) and Blinder decomposition methods. But what is almost invariably missing from the Oaxaca-Blinder studies is an independent and reliable measure of productivity. By contrast, in this project we used firm-level direct measures of productivity and wage differentials. Under proper assumptions the comparison of these two estimates provides a direct test for wage discrimination. One advantage of this approach is that it avoids identifying as discrimination wage differences that can be ascribed to productivity differences.

The importance of human capital in boosting productivity (and employability)

Groups displaying poor labour-market outcomes could suffer from a lack of employability (see point d above). The point is that the latter can be corrected/compensated. Leaving aside the question labour cost, a lack of productivity can be compensated by additional provision/production of human capital (more formal education, company-based training...). The point is again that these human-capital centric assumptions have insufficiently been examined at the level where productivity matters the most: firms. This is precisely what has been achieved by the EDIPO project. Moreover, the incidence and earnings effects of educational mismatch are well documented in the economic literature and findings are quite consistent. They notably show that, in a given job with a specific level of required education, over- (under-) educated workers earn more (less) than those who have just the required education for the. In contrast, the evidence regarding the impact of over- and under-education on firm productivity is mixed, indirect and subject to various potential biases – the EDIPO project has addressed this gap in the literature (Chapter 8).

Combining policy relevance with scientific excellence

The EDIPO research has not only addressed issues of extremely high policy relevance for the Belgian labour market, but it has done so in a way that contributed also to academic debates at the international level. The following list of papers (most of them already published), produced within the EDIPO project reflects the quality and quantity of work that has been done. The list below presents the scientific articles of EDIPO researchers as well as the scientific outlets that have published them.

- Garnero A., Kampelmann S. and Rycx F. (2014), "Part-time Work, Wages and Productivity: Evidence from Belgian Matched Panel Data", **Industrial and Labor Relations Review**, Vol. 67, No. 3, pp. 926-954.
- Garnero A., Giuliano R., Mahy B. and Rycx F. (2015), "Productivity, Wages and Profits Among Belgian Firms: Do Fixed-Term Contracts Matter?, R&R at **International Journal of Manpower**.
- Garnero A., Kampelmann S. and Rycx F. (2014), "The Heterogeneous Effects of Workplace Diversity on Productivity, Wages and Profits", **Industrial Relations: A Journal of Economy and Society**, Vol. 53, No. 3, pp. 430-477.
- Giuliano R., Kampelmann S., Mahy B. and Rycx F. (2015), "Short Notice, Big Difference? The Effects of Temporary Employment on Firm Competitiveness Across Sectors", submitted.
- Kampelmann S. and Rycx F. (2012), "The Impact of Educational Mismatch on Firm Productivity: Evidence from Linked Panel Data", **Economics of Education Review**, Vol. 31, No. 6, pp. 918-931.
- Kampelmann S. and Rycx F. (2015), "Wage Gaps Are Moving Targets: New Measurements of Wage Discrimination Against Foreigners with Firm-level Data", accepted at 4th EALE-SOLE World Conference, Montreal, July.
- Konings J., Rycx F. and Vandenberghe V. (2015), (*Mis)Alignment of Productivity and Wages: Firm-level Evidence - Introduction*, **International Journal of Manpower**, forthcoming.
- Konings J., Rycx F. and Vandenberghe V. (2015), (*Mis)Alignment of Productivity and Wages: Firm-level Evidence*, **International Journal of Manpower**, forthcoming.
- Mahy B., Rycx F. and Vermeylen G. (2015),"Educational Mismatch and Firm Productivity: Do Skills, Technology and Uncertainty Matter?", **De Economist** (Netherlands Economic Review), Vol. 163, No. 2, pp. 233-262.
- Konings, J. Marcolini, L. and Van Beveren (2014), "International Rent Sharing and Takeovers", R&R at **International Journal of Manpower**.
- Konings, J. and Vanormelingen, S. (2015). "The Impact of Training on Productivity and Wages: Firm Level Evidence", **Review of Economics and Statistics**, Vol. 97, No. 2, pp 485-497.
- Vandenberghe, V. (2015), Ageing. Can more Experience, Education and ICT Boost TFP Growth?, to be submitted.
- Vandenberghe, V. (2015), Is Workforce Diversity Good for Efficiency. An Approach Based on the Degree of Concavity of the Technology (2015), R&R in **International Journal of Manpower.**
- Vandenberghe, V. & A. Ariu (2014), "Assessing the Role of Ageing, Feminising and Better-Educated Workforces on TFP Growth", submitted.
- Vandenberghe, V & G. Specchia (2014), "Is Part-Time Employment a Boon or Bane for Firm Productivity ?", to be submitted.
- Vandenberghe, V. & L. Lebedinsky (2014), Assessing education's contribution to productivity using firm-level evidence", **International Journal of Manpower**, Vol. 35,

No. 8, pp. 1116-1139 (selected by the journal's editorial team as the Outstanding Paper of 2014).

Structure of the report

The structure of the report reflects the different at-risk groups that the EDIPO project set out to analyse. After presenting the general methodological framework in Part I, Part II is concerned with the labour market outcomes of women who work in Belgium. Part III summarises our findings regarding individuals with human capital lacunae and educational mismatch. Part IV discusses the position of individuals with foreign background on the Belgian labour market. Finally, Part V looks at the effect of diversity of workforce compositions and employment contracts for firm-level outcomes.

PART I – The EDIPO framework

CHAPTER 1 – Theories on wage inequality and productivity

1. What is wage discrimination?

The conventional definition of wage discrimination in labour economics is inseparably linked to the notion of productivity. According to the definition of Heckman (1998), wage discrimination corresponds to a situation in which an employer pays a different wage to two otherwise identical individuals but who differ with respect to a characteristic such as gender or race – with the crucial qualification that these characteristics have no direct effect on productivity.

A mismatch between wage gaps and productivity gaps may arise for different reasons, the classical explanations provided by Phelps (1972) and Arrow (1973) being 'statistical discrimination' and 'preference-based discrimination'. The first theory refers to the effect of negative stereotypes or a general lack of information of employers on the productivity of certain groups of workers, a situation that can turn into a "self-fulfilling prophecy" if it decreases the expected returns on human capital investments made by these workers (Aeberhardt and Pouget 2010: 119). In other words, due to employer beliefs or the limited transferability of credentials, some workers may be penalized for difficulties in signaling their productivity. The second theory refers to a situation in which the tastes of employers (or their employees or customers) translate into lower demand and lower wages for certain types of workers workers. A third theory on wage discrimination relates to differences in career dynamics, for instance if self-selection and self-censorship leads to some groups of workers behaving differently from their colleagues with identical productivity (Borjas 1987; Duguet et al. 2010: 7).

Starting from these premisses, it is obvious that empirical research needs data on wages but also on productivity to be able to assert the presence of discrimination. Recent advances in empirical research have provided at least three types of plausible explanations for productivity differences within the workforce. These explanations can be divided into a) intrinsic productivity differences; b) segregation into groups with different productivity; c) productivity differences between firms; and d) productivity spillovers.

2. Why does productivity differ among workers?

In this section we present in more detail each of the four generic explanations for why workers might differ with respect to their productivity. We will illustrate the underlying mechanisms by using the example of productivity differences between native workers and foreigners.

2.1. Intrinsic productivity differences

Intrinsic productivity differences refer to the value of the human capital or ability of some workers. They have for instance been documented in studies on the language abilities of immigrants (Chiswick 1991; Chiswick and Miller 1995, Dustmann and van Soest 2002, Hellerstein and Neumark 2003), literacy skills (Ferrer et al. 2006) or the quality and transferability of foreign education and training (Bratsberg and Ragan, 2002).

According to Friedberg (2000: 221), education and labor market experience acquired abroad are "significantly less valued than human capital obtained domestically". According to his study on the Israeli labour market, "this difference can fully explain the earnings disadvantage of immigrants relative to comparative natives". Bratsberg and Ragan (2002: 63) document a link between wage penalties and foreign education for the US. Their study suggests that this effect is either due to the inadequacy of foreign education or signaling problems and show that any additional schooling in the US "upgrades or certifies education received in the source country". More recently, Aeberhardt and Pouget (2010: 130) found that in the French wage distribution "the main differences between national origins lie in the returns to qualifications". Results in Dustmann and van Soest (2002) based on panel data from Germany show that "language proficiency is far more important than suggested by the existing literature". A key result of this line of research is that a substantial portion of observed wage differentials is linked to intrinsic productivity differences, but also that wage penalties could diminish over time if intrinsic differences taper out in the assimilation process. A serious limitation of research in this area is that only few studies use direct information on productivity and investigate gender biases in intrinsic productivity differentials between foreigners and natives (Hellerstein and Neumark 2006; Bartolucci 2014).

2.2. Segregation into categories with different productivity

A second source of productivity differences between different groups of workers can be subsumed under the concept of segregation, i.e. non-random sorting into categories with different productivity. The most common categories associated with segregation include job types, tasks, occupational nomenclatures, firms with different technologies or capital endowments and sectors of activity. Whereas intrinsic productivity effects refer to differences within the same category (e.g. unequal productivity within the same occupation), segregation points to differences in the distribution of workers across categories that each capture a certain level of productivity (e.g. overrepresentation of foreigners in occupations with lower productivity).

Bayard et al. (1999) argue that large parts of the wage gap between whites and non-whites in the US can be attributed to different types of labor market segregation. Elliott and Lindley (2008) conclude that occupational segregation contributes to immigrant-native wage gaps in the UK. Similarly, Aeberhardt and Pouget (2010: 118) find "no wage discrimination, but a certain degree of occupational segregation" in their matched employer-employee data from France. Aydemir and Skuterud (2008) use Canadian matched employer-employee data to document non-random sorting of immigrants into firms that pay lower wages, an effect that appears to be stronger for immigrant men than for women. Peri and Sparber (2009: 135) use US Census data from 1960-2000 to show that "foreign-born workers specialize in occupations that require manual and physical labor skills while natives pursue jobs more intensive in communication and language tasks", which can be interpreted as sorting into jobs with different productivity. Findings by Aslund and Nordstöm Skans (2010) suggest that path dependency can explain part of heterogeneous sorting in Sweden as immigrants are more likely to work in firms which already employ immigrants.

Although segregation does not fall under 'wage discrimination' in the sense of Heckman's definition quoted above, recent research suggests that labour economists have overlooked that segregation not necessarily "explains" observed wage differentials. Firstly, studies using firm-level panel data on productivity conclude that it is not clear to what extent categories such as occupations are actually accurate proxies for productivity (Gottschalk 1978, Kampelmann and Rycx 2012). Indeed, none of the studies cited above use direct measures of productvity and therefore have to rely on more or less accurate proxies. Secondly, non-random sorting is hardly a satisfying explanation but rather points to structural differences in terms of origin or gender that call themselves for explanations. For instance, segregation raises equity issues if some workers are systematically "downgraded" into low-wage categories that lie below their observed skills, as suggested in recent work by Dustmann et al. (2013) and McGuinness and Byrne (2014). As mentioned above, most available studies on gender or ethnic biases in segregation suffer from the absence of direct productivity measures (Hellerstein and Neumark 2006; Bartolucci 2014).

2.3. Between-firm productivity differences

Productivity differences occur not only at the individual level, but also between firms. This has potentially important ramifications for the study of poverty and wage inequality that we will briefly introduce in this section.

The analysis of wage inequality is traditionally done using individual-level surveys (EU-LFS, EU-SILC…). But the firm-level dimension of wage inequality, driven by firm-level productivity differences, is also a research topic worth considering. Such a claim rests on the theoretical prediction that wages should reflect productivity, but also empirical evidence — mainly at the macro level — that wage growth is indexed on productivity growth. There is also that recent works, covering the situation of English-speaking advanced economies, highlight a growing propensity of wage inequality to take place between firms within industries rather than within firms. As far as we know, an investigation of the determinants of the "between" firm rather than "within-firm" configuration of wage inequality has never been carried out in Belgium.

We now examine whether, over the past decades, the Belgian private economy has experienced a rise of firm-level productivity dispersion that could ultimately translate into rising wage inequality.

The role of productivity in explaining wages

Using Bel-first data we are able to follow 7,894 firms during the 1998-2011 period (14 consecutive years). A first results, visible in Table a1, is that firm-level estimates of productivity are relatively good predictors of the average annual ou hourly wage paid by the firm. Using the total variance (intra and inter firm), one finds an elasticity superior to .4. And what is more, it is fairly stable across the years. Table a1 (right-hand columns) also reports the estimates of the same elasticities, but solely based on the variations that have taken place inside (or within) firms. Technically, this means that the estimated equation comprise a firm fixed effect. The magniture of the elasticity between productivy (changes) and wage (changes) is slightly lower, ranging from .25 to .35.

Table 1.1 – Elasticity of annual wage (labour cost per unit of labour) to annual productivity (value-added per unit of labour). Evolution from 1998 to 2012

	Between & within firm variations		**Within firm variation only**	
Year	**Unit of labour =employee**	**Unit of labour= hours**	**Unit of labour =employee**	**Unit of labour= hours**
1998	0.50	0.38	0.31	0.28
1999	0.44	0.38	0.31	0.28
2000	0.44	0.36	0.32	0.27
2001	0.50	0.39	0.32	0.26
2002	0.50	0.40	0.33	0.25
2003	0.50	0.39	0.34	0.24
2004	0.50	0.41	0.34	0.24
2005	0.50	0.41	0.34	0.23
2006	0.48	0.43	0.35	0.22
2007	0.44	0.42	0.34	0.23
2008	0.44	0.39	0.34	0.22
2009	0.43	0.36	0.35	0.20
2010	0.43	0.38	0.35	0.20
2011	0.45	0.42	0.36	0.19

Source: Belfirst 1998-2011: #firms followed = 7894

The evolution of productivity differences across firms

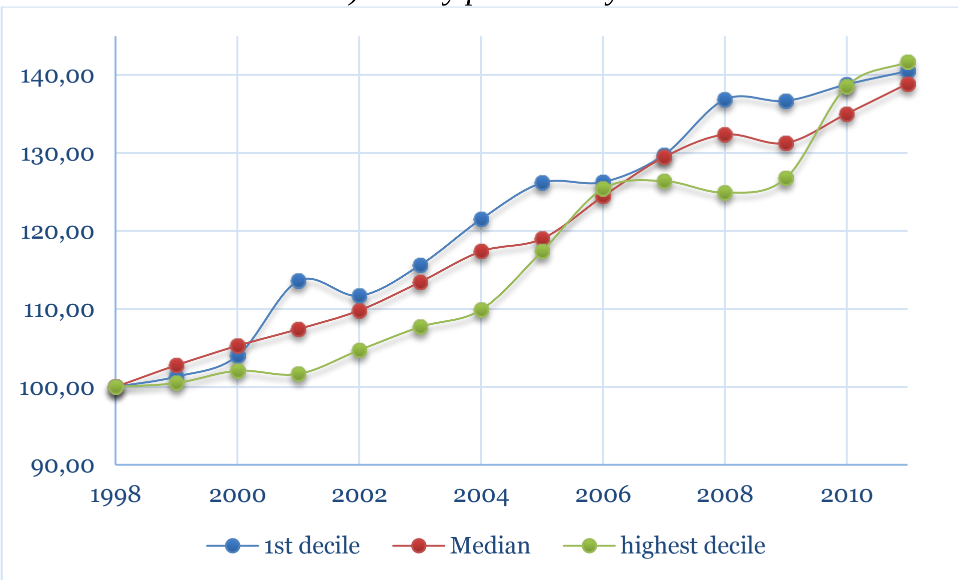
Establishing the link between wages (level growth) and productivity (level growth) at firm-level is interresting. But the key purpose of the exercise is rather to assess, in the case of Belgium, the propensity of labour productivity differences across firms to rise over time. The evidence for English-speaking advanced economies for instance is that of an expanding productivity gap across firms that has contributed to the overal rise in wage inequality. Faggio, Salvanes & Van Reenen (2010) show that within-industry productivity dispersion in the UK and the USA has trended upwards over the past decades. And they relate this increased productivity dispersion to the growth in wage inequality that has occurred over the same period in the UK and the USA. We are interested here to see if a similar productivity spreading is occurring in Belgium.

To insvestigate that, using our Bel-first panel, we focus on the evolution over time of productivity at different points of the overall productivy distribution; namely the lowest decile (10%), the median (50%) and the upper decile (90%). The results are displayed in Table a.1 and on Figure a.1. The key result is that productivity gains seem to be of very similar magnitude across the deciles — particulary if one abstract for short-term divergences. The tentative conclusion is thus that productivity inequalities have stayed relatively stable over the past 2 decades, and — conditional on no changes in the wage/productivity relationship — have not contributed to a rise in wage inequalities.

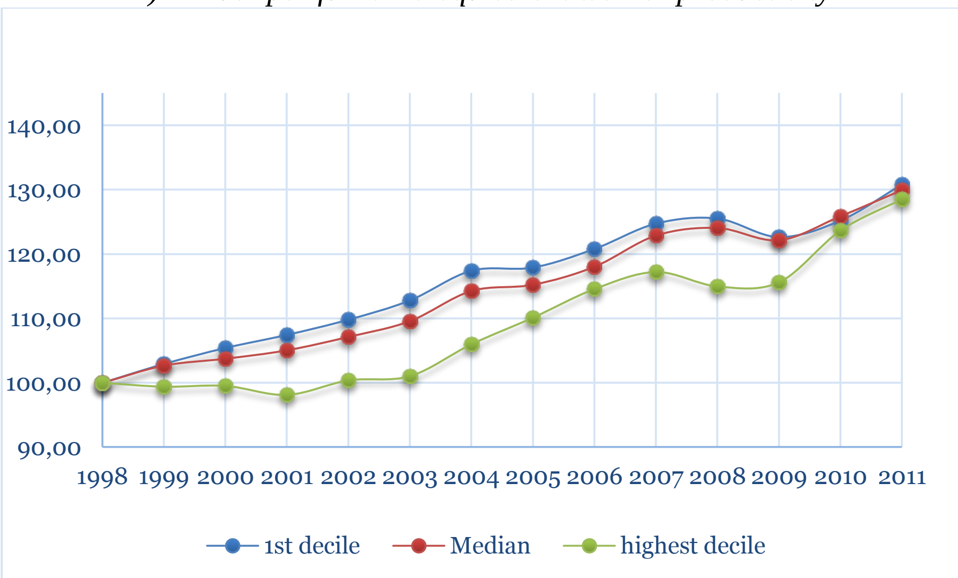
We obtain similar results when computing the evolution of the *coefficient of variation* of both annual productivity per full-time equivalent worker and hourly productivity or the *productivity ratio between the highest (90%) and the lowest (10%) deciles* of the distribution (Table a.2). Referring to the annual productivity (ie. value added) per worker, the latter ratio has remained fairly stable; from 3.19 in 1998 to 3.23 in 2011.

Figure 1.1 – Evolution of labour productivity. Breakdown per decile.

i) Hourly productivity



ii) Annual per full-time-equivalent worker productivity



Source: Bel-first 1998-2011; : #firms followed = 7894

Table 1.2 - Productivity per unit of labour.
Coefficent of variation and highest/lowest decile ratio.
Evolution from 1998 to 2011

	Coeff. Variation$		**Highest/lowest deciles ratio**	
year	**Annual produtivity of a fte* worker**	**Hourly productivity**	**Annual produtivity of a fte worker**	**Hourly productivity**
1998	82.70	96.12	3.19	2.93
1999	77.42	87.29	3.14	2.93
2000	73.94	83.43	3.15	2.97
2001	70.30	86.47	3.05	2.86
2002	72.12	79.62	3.02	2.81
2003	70.95	79.66	3.04	2.79
2004	70.44	78.61	3.06	2.80
2005	74.75	84.56	3.06	2.83
2006	75.34	85.00	3.06	2.88
2007	72.36	87.60	3.16	2.97
2008	69.43	85.71	3.14	2.93
2009	71.60	81.95	3.21	2.90
2010	75.60	93.86	3.31	3.02
2011	76.25	87.22	3.23	3.02

$: standard deviation/mean; * full-time equivalent

Source: Bel-first 1998-2011; : #firms followed = 7894

2.4. Productivity spillovers

A fourth source of productivity differentials between different groups of workers are spillover effects, i.e. the impact of a worker on the productivity of his or her co-workers. Both intra- and intergroup spillovers are plausible and have been documented in the literature. The former has been mainly linked to common language or shared social norms that lead to positive spillovers on the productivity of other migrants (Lazear 1999, Hellerstein and Neumark 2008). Similarly, Giuliano and Ransom (2013: 376) posit the existence of "production complementarities" among foreign employees given that "ethnic similarity facilitates training". Intergroup spillovers are closely related to the literature on workforce diversity that has studied the firm-level productivity effects of heterogeneous workers (Alesina et al. 2003, Garnero et al. 2014b, Parotta et al. 2014). The observation by Peri and Sparber (2009) that native workers tend to react to the increased supply of manual immigrant labour by specializing in communication-intensive tasks can also be interpreted as an intergroup spillover effect. In general, spillovers raise the question to what extent diversity translates either into complementarities in terms of skills, task specialization, language proficiency, knowledge of different markets and networks etc or, on the contrary, increases co-operation costs due to frictions within a more heterogeneous workforce.

Ottaviano and Peri (2012: 152) find evidence for negative intra- and positive inter-group spillovers and argue that immigration in the US has “a small positive effect on average native wages (+0.6%) and a substantial negative effect (-6.7%) on wages of previous migrants in the long run”. Mitaritonna et al. (2014: 1) use French micro-level data to show that “a supply-driven increase in foreign born workers in a department (location) increases the productivity of firms in that department”, whereas Nicodemo (2013) finds negative productivity effects of immigrations in matched employer-employee data from Spain. These studies do not, however, distinguish whether this effect can be attributed to spillovers or whether immigrants have a different productivity than natives. Böheim et al. (2012: 3) work with administrative data from Austrian and provide evidence for a strong positive effect of worker heterogeneity and a negative effect of the share of the worker's own ethnic group on wages. The authors interpret this result in terms of positive intergroup productivity spillovers due to production complementarities.

Spillover effects pose interesting conceptual challenges to Heckman’s definition of wage discrimination. In line with conventional wage theory, Heckman defined the appropriate level of remuneration in terms of the value of individual labour productivity and does not discuss how spillovers to the labour productivity of other workers should be retributed. Perhaps even more importantly, the relationship between potential spillovers of foreigners and wages has been hampered by the limited availability of data on firm-level labour productivity: the datasets used by Ottaviano and Peri (2012) and Böheim et al. (2013) contain no direct measure of labour productivity, and Mitaritonna et al (2014) can only use total factor productivity in a sample restricted to manufacturing firms. And while the dataset used by Nicodemo (2013) contains direct measures of firm-level productivity the study does not relate these spillovers to wages. Building on recent advances in empirical methods, the next section presents our empirical approach that arguably provides for a more satisfactory treatment of firm productivity in the analysis of poverty and wage inequality.

CHAPTER 2 – Measuring wages and productivity with firm-level data

In this section we present the shortcomings of the conventional approach of comparing productivity and wages with the so-called Oaxaca-Bilder decomposition. We then present an alternative approach based on the estimation of firm-level productivity and wage equations. The different methods are illustrated with examples taken from the literature.

1. The conventional approach for comparing productivity and wages

Over several decades the contributions by Oaxaca (1973) and Blinder (1973) have provided the most commonly used tools for studying potential wage discrimination against foreigners. The Oaxaca-Blinder method compares individual-level Mincer-type equations for natives, foreigners and a hypothetical reference group and decomposes the observed wage differentials into human capital or compositional differences and an "unexplained" residual. To the extent that individual productivity can be proxied as a function of observable characteristics, the residual can be interpreted as a gap between wages and productivity (Altonji and Blank 1999). The manifold applications of this method generally conclude a) that a substantial portion of the foreigners' wage penalty can be attributed to intrinsic productivity differences and sorting into occupations and sectors with lower wages; and b) that the residual gap is significantly positive and therefore suggests wage discrimination.

As a tool for disentangling productivity and wage discrimination, the standard version of the Oaxaca-Blinder decomposition has attracted increasingly sharp criticism (Hellerstein and Neumark 2006). First, by definition the residual gap confounds any unobserved intrinsic productivity differences or unobserved sorting with discrimination. Second, the method controls for differences in occupational or sectoral composition between natives and foreigners rather than explaining the process of sorting into groups with different productivity; it is therefore prone to a "potential selectivity bias" (Aeberhardt and Pouget 2010: 119). Third, the individual-level equations of the Oaxaca-Blinder framework ignore productivity spillover effects that occur at the level of the firm. The conclusion that Bartolucci (2014: 3) draws from this is harsh: "As discrimination has normally been detected through the unexplained gap in wage equations and this approach is not the best option for disentangling differences in productivity and discrimination, there are few papers that address labor market discrimination against immigrants."

2. Supply and demand

We can use the example of the labour market for senior workers to illustrate how our framework addresses supply and demand effects related to different types of workers.

The existing economic literature primarily covers the supply side of the old-age labour market. It examines the (pre)retirement behaviour of older individuals (Mitchell & Fields, 1984) and its determinants, for example how the generosity of early pension and other welfare regimes entices people to withdraw from the labour force (Saint Paul, 2009). In the Belgian case, there is strong evidence that easy access to early retirement benefits and old-age pension systems made it financially unattractive to work after the age of 55. The implicit tax on continued work has risen strongly since the 1960s and has played a significant role in the drop in the employment rate among older individuals (Blondäl & Scarpetta, 1999; Jousten *et al.*, 2008). Other papers with a supply-side focus examine how poor health status precipitates retirement (Kalwij & Vermeulen, 2008) or the importance of non-economic factors (i.e. family considerations) in the decision of older women to retire (Pozzebon & Mitchell, 1989; Weaver, 1994).

The demand side of the labour market for older individuals has started to receive some attention from economists. Some have started examining the relationship between age and productivity at the level where this matters most: firms. They have estimated production functions expanded by the specification of a labour-quality index à la Hellerstein & Neumark (1995a,b) (HN henceforth). According to Malmberg *et al.* (2008), an accumulation of high shares of older adults in Swedish manufacturing plants does not negatively impact plant-level productivity. By contrast, Grund & Westergård-Nielsen (2008) find that both mean age and age dispersion in Danish firms are inversely U-shaped in relation to firms' productivity. But these authors use cross-sectional approaches. More recent analysis of the German evidence by Göbel & Zwick (2009), using panel data to control for the endogeneity of age structure, produces little evidence of an age-related productivity decline. By contrast, Lallemand & Ryck (2009), who use Belgian firm-level panel data, conclude that older workers (>49) are significantly less productive than prime-age workers, particularly in ICT firms.

3. The impact of globalisation on wages and rent sharing[1]

An important factor influencing both the productivity and the remuneration of workers is globalisation. In this section we present evidence on the firm-level aspects of globalisation through an analysis of the relationship between take overs by multinationals and the way that economic rents are shared between capital and labour.

Foreign multinationals are more footloose than domestic multinationals and purely domestic firms, thanks to their possibility of relocating production abroad. This fact may make the multinational firms less likely to make long-term investments such as in-depth training of staff, or decrease the bargaining power of workers versus the firm in negotiations regarding remuneration or work conditions.

The purpose of this section is to clarify the impact of foreign acquisition on wages of workers in the acquired domestic firm, through a specific channel, i.e. rent sharing. A key question in international business and economics is how firms and their economic environment are affected when foreign firms invest in a country, in the form of so-called Foreign Direct Investment (FDI). When a firm invests through FDI, it acquires direct control of a firm abroad, either by setting up a firm from scratch, or by obtaining partial or full ownership of an exiting firm. FDI is typically classified as either being horizontal, when a firm acquires or sets up a firm abroad with broadly the same type of activity; vertical, when the foreign firm performs upstream activities such as providing materials or downstream activities such as sales. Less frequent are acquisition of foreign firms with unrelated activities such as in a conglomerate. In all three types the direct control of the foreign firm is key, and FDI therefore differs from other less direct types of international investments such as investment in equity through the stock market.

Economists have been exploring the consequences of inward foreign direct investment (FDI) in a domestic economy for many years now. An important question which has been considered, is the performance of foreign-owned multinational corporations (MNEs) and the effect of their existence on the host country. It has now been established that inward FDl assists the transfer of technology

[1] This section is a based on Konings, Marcolin and Van Beveren (2014), which tunes in more on the technical details and methodology.

from the foreign to the domestic country. This may occur through the introduction of tangible goods with embedded technology such as advanced capital goods (such as machinery or intermediary goods used in production, for example chips which go into a printed circuit board) but also through less tangible technological transfer such as through the introduction of new organizational structures and the exposure to new business practices. They also promote competition in the domestic market for inputs which are used by the multinational firm, such as labor and materials, thus potentially leading to lower prices, quality improvements and innovation. MNEs moreover contribute in raising the skill level of the host country workforce, by exposing workers to more advanced technologies and offering on-the-job training.

Rent sharing differs from profit sharing because of several reasons. The firm might not be willing to consider sharing all of the profits with workers, for example because the firm has alternative options such as relocation. Only the "surplus profit", which is the profits in excess of the best alternative the firm has in case negotiations break down, are up for negotiation, and it is this surplus which is referred to as the "rent". The profits that are referred to, do not necessarily coincide with accounting profits. If a firm has made a large sunk investment (say in heavy machinery for exploitation of an iron mine), there might still be rents to be bargained over although the accounting profits can be negative in times of a serious economic downturn. The workers might still be able to negotiate over rent sharing even if current profits are negative, simply because the outside option of the firm is a very costly alternative (closing the mine down is costly). In this paper we will use EBITDA (earnings before interest taxes depreciation and amortization) as a proxy for the rents over which can be bargained. As a robustness check we test our hypothesis using two other definition of profits: profits after taxes and operating profits.

Earlier literature in rent sharing has tended to focus on rent sharing within the same firm and country such as, for instance, in Blanchflower et al. (1996). We will refer to this type of rent-sharing as "domestic" rent sharing. Budd and Slaughter (2004) were the first to separately consider both domestic and international rent sharing, by extending the theoretical framework of Blanchflower et al. (1996) to allow for profit sharing across international borders. Using data on US and Canadian union wage contracts, their empirical findings suggest that domestic profit sharing occurs mainly with workers of domestic firms, while cross-border profit sharing seems to be limited to workers employed by US-owned multinational firms. Budd et al. (2005) developed an alternative theoretical model that generates similar empirical predictions; they were also the first to explore the existence of multinational and domestic rent sharing at the firm-level, using Amadeus data on European parents and their European affiliates. Their estimations point to the existence of domestic and international (from parent to affiliate) rent sharing in multinational firms. Martins and Yang (2010) extend this framework to 47 countries worldwide, whereas Martins (2009) and Rusinek and Rycx (2011) tested it at the national level in Portugal and Belgium respectively.

While the literature has established the existence of both a domestic and international rent sharing mechanism, it sheds no light on how a change in ownership (nationality) of a firm changes the rent sharing relationship between the firm and its domestic and foreign workers. In other words, this literature has focused on a post-acquisition environment. It can be argued, however, that a change in ownership will negatively affect the relative bargaining power of the workers, hence reducing the degree of domestic rent sharing (see for example Rodrik, 1997, for supporting arguments). On the other hand, if foreign owned firms are able to generate rents thanks to their firm-specific assets, they may be willing to share them with their workers by offering non-competitive wages, independently on the quality of employed workers. This would be the case, for instance, if the firm wants to enhance workers' efforts and loyalty, or if they want to minimize the frictional costs caused by belligerent employer-employee relations. This ambiguous intuition is reflected in the variety of results found by the empirical literature on the impact of takeovers on firms' wages. Almeida (2007), Huttunen (2007) and, more recently, Weche-Geluebcke (2012) find a positive sign for foreign acquisition effect in Portugal, Finland and Germany; similarly, Oberhofer et al. (2012) extend the analysis to 16 European countries, and find a positive sign for Eastern European countries in particular. Heyman (2011), on the other hand, find that foreign acquisitions also impact negatively the lower end of the wage distribution, contrary to Lipsey and Sjoeholm (2004), where only blue collar workers in Indonesia gain in salary from such deals. Girma and Goerg (2007) look at the UK and find an increase in wages only for skilled workers, or for both skilled and unskilled in the case of US acquirers. Besides finding an ambiguous sign for the impact of foreign acquisition on wages, this literature has hardly explicitly tested the channel through which this effect would take place.

The main purpose of the present paper is to investigate how a foreign takeover influences the relative bargaining power of workers and hence the degree of domestic rent sharing, while taking into account the existence of international profit sharing. We do so focusing on takeovers targeting Belgian companies from 1998 to 2010. Using takeover data collected from Bureau van Dijk (Zephyr dataset) and other firm level information, we can correctly identify M&As, and in particular the ownership of both acquirers and targets, and the transferred control share. What is more, we manage to exclude from our sample domestic firms which are already subsidiaries of a foreign group. We then adapt the empirical framework in Budd et al. (2005) to a takeover setting and estimate it. Thanks to the availability of both acquirer and target firm information, our empirical setting allows to distinguish between the rent sharing contribution to wages of both the domestic and the foreign company.

Of course, directly comparing acquired and non-acquired firms is not sufficient to retrieve the unbiased effect of rent sharing, due to the possibility that acquired firms have different characteristics than non-acquired firms, which are correlated with the probability of takeover. In order to avoid this selection bias, we compare the treated group (i.e. the acquired firms) with a sub-sample of the non-acquired Belgian firms, which are similar in size, age, capital intensity and productivity to the treated sample. This is done by creating a so-called "propensity-score" index using the aforementioned variables, which summarizes the likelihood of any firm in the sample to be acquired. We then consider the change in rent sharing behavior of the acquired firm before and after the takeover, and compare this to the dissimilarity in rent sharing between target firms and the "matched" control sample.

3.1 Empirical specification

The main aim of our analysis is to highlight differences in profit sharing before and after a takeover of a Belgian firm by a foreign company. In our estimations we control for the firm specific share of skilled workers, because a firm may change its skill mix after a takeover. If multinationals are more efficient with higher profits and employ more skilled workers, we would observe both a higher average wage and higher profits after a takeover. This would lead us to spuriously conclude there is evidence for rent-sharing. By including the share of skilled workers in the analysis and separately estimating its effect, we avoid this mistake. Another variable for which we control in our analysis the firm-specific ratio of capital to labor (fixed assets over employment). A change in the firm's capital intensity after the takeover may simultaneously affect profits and wages, since capital intensity is positively correlated with the skill level of the labor force (Griliches, Duffy et al. 2004). It is important to include these controls, to avoid confounding these effects with the estimation of the effect on rent-sharing. We expect a positive effect for both controls. We will present specifications with and without them.

As industry composition and macroeconomic conditions may also affect wages, we allow for separate industry and year effects in our estimation equation. As with the inclusion of controls for capital intensity and skill composition, the inclusion of these industry and year effects should also aid to avoid confounding effects from biasing our estimated effect on rent sharing. Similarly, we want to avoid firm-specific factors to bias our results, and we therefore allow for arbitrary time-invariant firm-specific factors in our estimation. This is equivalent to estimation using only differences in all variables over time, thus eliminating any effect of such time-constant factors. This purges our results from the effect of important time invariant unobserved differences between firms, such as firm efficiency, workers features other than skill, or preferences of union workers over the reservation wages. Finally, we utilize statistical methods which take into account that the different observations which are made on a single firm over time may not be perfectly independent, to avoid overestimating the precision of our estimated effects. The results of this exercise will provide a first idea on the existence of domestic and international profit sharing in our data, thus aligning our research with previous results in the stream of literature.

An important problem is that this estimation neglects the fact that the targeted firm has information before the takeover and might have changed its rent sharing behavior after the takeover. We therefore will also estimate taking the time of takeover into account, separately estimating an effect of rent-sharing before and after the takeover on the sample of firms which has been acquired at some point. Through the use of the “propensity score” and the estimation before and after the takeover, we can also take into account the possibility that the acquirer is buying a specific target also considering the target’s wage setting practices.

We will then estimate profit sharing comparing two groups of firms: firms which were at some point acquired versus the group of local firms which were never acquired. This is called a “difference-in-difference” approach, where the first difference refers to changes in profits and the effects on wages (profit sharing) before and after the takeover; and the second difference refers to investigating how this effect differs between both groups (acquired versus non-aquired firms).

In all of our analysis we will control for the profits of the acquiring parent to investigate the possible existence of international profit sharing in acquired firms.

In order for the above to be estimated without bias, it is however necessary to take into account the existence of selection. Simply comparing outcomes for merging and non-merging firms may suffer from selection problems, since the two groups may be differentiated by some unobservable characteristics which simultaneously affect the probability of the takeover and wages. It is therefore impossible to assume that firms subject to foreign takeovers are randomly drawn from the population of domestic firms. It is indeed very likely that the choice of the company to target is influenced by the characteristics of the target company itself, or its market. It is possible that the company is targeted because it is operating especially well (“cherry picking” takeovers) or especially poorly (the target is a “lemon”). In order to avoid any selection bias, we therefore implement a “propensity score” matching procedure: by estimating the probability for company to be acquired given a set of observables, it is possible to pair each “treated” firm with one (or more) domestic firms which was not acquired but had similar observable characteristics, or at least a set of characteristics that lead to the same probability (or propensity) to be acquired. Rosenbaum and Rubin (1983) demonstrated that a sufficient matching quality can be reached by pairing treated and control observations based on the units’ individual “treatment” probabilities (the propensity scores) rather than the full set of variables.

We estimate the probability of being acquired by a non-Belgian company using a set of target characteristics in the time period before the acquisition. The choice of such characteristics was based upon the existing literature and economic intuition, conditional on data availability. This resulting propensity score needs to satisfy the Conditional Independence Assumption (CIA), whereby the outcome variable must be independent on treatment, conditional on propensity score. This translates into choosing firm-level characteristics which affect both the final outcome and the treatment decision, but which are independent from the treatment itself (Caliendo and Kopeinig, 2008). The variables are therefore lagged once. Our chosen variables turned out to be significant in predicting takeovers, with the exception to the capital-labor ratio, which was kept despite its insignificance to match what has been previously done by the literature. The validity of the CIA is further confirmed with an appropriate statistical test.

3.2 Data and descriptive statistics

We exploit firm level information contained in four different datasets provided by Bureau van Dijk. From Zephyr we downloaded all cases of mergers and acquisitions (M&As) involving a Belgian target from the year 1998 to 2010; the dataset contains information on merger and acquisitions deals from all over the world, as well as certain financial indicators for targets, acquirers and vendors of the deal; it also contains a firm level identifier for all involved companies, so that it was possible to combine the information from this dataset with firm accounting information from other datasets. In particular, we extracted balance sheet and ownership information for Belgian companies involved in the deals from the Belfirst dataset (also from Bureau van Dijk). We downloaded data from 1996 to 2012, so that we have at least two years of unconsolidated balance sheet information before and after the deal for all target firms involved in M&As. We do the same for acquirers by exploiting Bureau van Dijk's products Amadeus (for European acquirers) and Orbis (for acquirers established elsewhere) for foreign acquirers, and Belfirst for domestic ones.

Zephyr includes information on different types of deals (acquisitions, mergers, initial public offerings, joint ventures, management buy-ins and buy-outs, institutional buy-outs, etc.), and there is no minimum deal value for being included in the dataset, which is advantageous with respect to the other often used M&A databases (Thompson Financial Securities). That is why from an initial number of 5627 deals involving at least a Belgian target, we restrict our final sample to 532 deals, 216 of which can be classified as cross-border, the remaining as domestic. In particular, we keep only the deals that involve a switch in the controlling ownership by the acquirer from less to more than 25 percent of outstanding shares. We chose this threshold as it guarantees important control rights over the acquired firm in many European countries, but we will experiment with it in later stages of the analysis. Deals involving institutional investors or private investors who were not organized as companies were also excluded, together with those for which it was not possible to retrieve at least two years of accounting information before and after the deal for the target firm.

The nationality of the targets has been checked and integrated with the use of the ownership data included in the same datasets, so as to exclude Belgian targets which are affiliates of foreign companies. These have been defined as a Belgian companies whose Global Ultimate Owner (ref. Bureau van Dijk definition) is foreign for at least 25 percent. Similarly, acquirers which were Belgian subsidiaries of foreign companies or foreign subsidiaries of Belgian companies were also excluded from the sample. Once the ownership of the buyer was thus defined, cross border acquisitions were identified as those involving a non-Belgian firm buying a Belgian firm, which had been Belgian at least at for two years before the acquisition, and keeping ownership of the firm at least for two years. Cross border acquisitions involved buyers from 24 different countries worldwide, although the vast majority of acquirers is located in Europe.

Finally, the dataset also contains accounting and ownership information for all Belgian firms which were not involved in an acquisition in the considered period and for which it was possible to trace information in Belfirst. These are 157,093 companies which constitute our "control" group. In the empirical analysis we include firms operating in all sectors except those classified with NACE revision 2 codes above 84, once outliers in wages and profits were dropped. Table 1 contains the sample composition per year.

Table 2.1

Year	**Domestic**	**Target**	**Foreign**	**Domestic**
1998	23,727	334	127	207
1999	25,867	365	139	226
2000	25,919	391	147	244
2001	26,138	385	137	248
2002	25,609	408	151	257
2003	26,820	408	149	259
2004	26,392	397	148	249
2005	24,308	393	154	239
2006	25,346	372	147	225
2007	24,594	353	143	210
2008	22,812	331	131	200
2009	21,026	312	120	192
2010	19,858	281	106	175

Financial data for Belgian companies have been deflated using time series of producer prices at the two-digit Nace revision 2 level provided by the "Steunpunt Ondernemen en Regional Economie" (STORE). In particular, wages and profits, as well as value added and sales, were deflated using the price of value added. Financial data for acquirers was deflated using the total producer prices for industrial goods provided by the OECD. For those acquirers were the provided time series did not sufficiently extend to the past or is missing, we used the consumer price index for the acquirer's country of origin. If this was not available either, we used the U.S. producer price index instead. In order to further net the estimation results for the coefficients of interest from price effects on the outcome variable, we control for year and target-industry fixed effects in all empirical specifications. Finally, we argue that industry-specific price dynamics should not affect our estimation results once the acquired firm is compared to a matched one, as the matches are taken from the same industry and year.

In our analysis, we use yearly firm level data for Belgian firms on turnover, wage costs, fixed assets, value added, employment, share of employment composed by skilled workforce, part time workers and male workers. The average firm wage is obtained by dividing the total firm-level annual wage bill by the number of full time equivalent employees, but we ran our baseline specifications using hourly wages as well. We construct the capital-labor ratio as the sum of tangible and intangible fixed assets over the number of full time equivalent employees. As a definition of profits we use EBITDA, calculated as operating profits adding back depreciation and amortizations. There are several reasons for this choice: first of all, this measure approximately corresponds to the concept of rents from production only, independent on financial profits or profits from other company activities. By taking profits before interest, taxes and depreciations, we also limit the scope of "strategic" misreporting by firms, which takes place thanks to the firms' discretionary power in declaring profits in different years and countries from the moment of profit realization. Thirdly, we enhance cross-country comparisons, considering the variety of accounting rules for depreciation and taxation in particular. Finally, by still including depreciations and amortizations, EBITDA cancels the effect of past takeovers on profitability, which would reduce profits if subtracted from revenues in the form of depreciation and amortizations.

Table 1.2

		Mean	**SD**
Sales	Target	51,950	231,427
	Domestic	5,261	14,703
Wages	Target	51.15	27.80
	Domestic	37.28	18.72
Profits	Target	59.03	155.60
	Domestic	37.71	92.02
K/L	Target	113.13	477.84
	Domestic	69.46	207.59
Productivity	Target	110.18	163.71
	Domestic	74.99	96.80
% Skilled	Target	0.64	0.34
	Domestic	0.44	0.42
% Male	Target	0.71	0.23
	Domestic	0.73	0.40
% Part time	Target	0.13	0.23
	Domestic	0.33	1.37

In Table 2 these variables are summarized, distinguishing between firms which were acquired by a foreign company from those which were never acquired (for simplicity "Target" and "Domestic" firms, respectively), averaging information before and after the acquisition. "Target" firms were found to sell on average significantly more than "domestic" firms, and to offer much higher wages. The table suggests multiple channels through which these differences in wages may rise: "target" firms are more capital intensive, more productive and more profitable than firms which were never part of an acquisition. What is more, they employ significantly more skilled and less part time workers, both of which can increase firm average wages.

This first descriptive evidence of the diversity between treated and control firms, however, may be invalidated by the existence of selection bias, if Belgian target firms were significantly different from non-target firms even before the acquisition. That is why we perform a test for the difference in means for target firms before and after the acquisition. The descriptive statistics are reported in Table 3: they suggest that firms subject to foreign takeover decreased size on average, but increased mean wages, productivity of labor, capital intensity and profits. The labor composition did not seem to change significantly.

Table 2.3

		Mean	**SD**
Sales	Before	54,579	247,927
	After	48,281	206,398
Wages	Before	45.86	15.73
	After	58.55	37.60
Profits	Before	47.89	104.32
	After	74.57	206.04
K/L	Before	72.66	141.74
	After	169.59	716.95
Productivity	Before	93.75	108.32
	After	133.11	216.75
% Skilled	Before	0.64	0.33
	After	0.65	0.35
% Male	Before	0.72	0.24
	After	0.70	0.22
% Part time	Before	0.13	0.27
	After	0.12	0.17

Profits and wages display remarkable variance: while this is not unlikely for profits, it is less obvious for wages. This evidence reflects the high variability in the type of firms which are acquired, ranging from small non performing companies to already established international competitors. In our estimation, however, we take precaution in mitigating the effect of outliers in wages by: (i) dropping firms with the 1% lowest and 1% highest wages, to remove possible faulty data; (ii) operate in logarithm of wages, rather than wages in levels (which is also supported by the literature); (iii) exploiting the matched sample technique.

3.3 EMPIRICAL RESULTS

This section presents our main results. We first report the result of a basic estimation which ignores the potential reverse causality and selection issues highlighted in the previous paragraphs.

We then report the outcome of the propensity score matching process, and the results of the analysis using the restricted (matched) sample.

Propensity score

We now present results based on the propensity score matching approach. Table 4b reports the outcome of a logit estimation for the probability of being "treated", i.e. being acquired by a non-Belgian company. The treatment is defined as the firm whose ownership is initially domestic (i.e. share of equity owned by foreign parties below 25%) and which, in some subsequent year, becomes foreign owned (above 25% foreign stake). The determinants of the treatment are included lagged once to allow for lagged effects of the explanatory variables on the takeover probability. The results are coherent with expectations: bigger firms have a higher acquisition probability everything else held constant, although second order negative effects of size are also found. Capital intensity does not seem to affect the probability of being taken over, contrary to the productivity and skill intensity of the workforce, which increase the probability of being acquired by a foreign entity. Older firms are less likely to be acquired, as well as more profitable ones. The fact that foreign acquirers are more likely to buy Belgian firms which perform relatively badly in earnings once their overall performance is taken into account might indicate that acquirers are looking for poorly managed or undervalued firms, under the belief that they will be able to operate the company better than the current management. The reported numbers for each variable correspond to the estimated percentage increase in the odds of being acquired, for a one percentage increase in the variable.

Table 2.4

Sales	**1.872*****
	(0.229)
Sales-squared	-0.0499***
	(0.0119)
Labor productivity	0.595***
	(0.114)
Capital intensity	0.00239
	(0.0310)
Age of firm	-0.248***
	(0.0536)
Prof	-0.363***
	(0.0547)
%skilled	0.869***
	(0.151)

Next, we estimate the effect of foreign acquisition on the target firm's wages using a difference-indifferences matching approach based on the estimated propensity score. We do so exploiting three common techniques to determine which observations are sufficiently close to an acquired firm to be useful as comparison firms, i.e. nearest neighbor, radius and kernel matching. We condition the matches to be in the same year and industry of the treated observation, and we impose the common support condition as specified above, with minimal loss of treated observations.

The first three rows in Table 4c show the effect of foreign acquisition of the average wage in the target firm one year after acquisition; the last three rows display the same, but for the percentage difference in the value of wages two years after the takeover and the year of the takeover.

Table 2.5

after one year:	**Effect**	**standard error**
Nearest Neighbour	0.0463	0.0156
Radius	0.0468	0.0155
Kernel	0.0477	0.0148
after two years:	**Effect**	**standard error**
Nearest Neighbour	0.1094	0.0186
Radius	0.1107	0.0190
Kernel	0.1099	0.0181

This is the average treatment of the treated (ATT), or the difference between the change in time of wages for control firms and for treated (i.e. acquired) firms. Takeovers have a small but positive and significant effect (4.5% to 11%) on the wages offered by the target company in the first two years after acquisition. The takeover premium is higher (and more significant) in the second year after the acquisition, which is coherent with the intuition that takeovers may require an adjustment period before changing the structure of the target company. This is especially important in the case of wages, which are disciplined under contracts which may not be immediately renegotiated by the acquirer company.

Difference-in-Difference and Rent Sharing

In what follows, we highlight the existence of one channel through which workers in the target company obtain a wage premium, i.e. rent sharing. Table 5 reports the results of estimating profit sharing using only the matched sample, using OLS and fixed effect panel estimation. Under all specifications, the hypothesis of positive domestic rent sharing before the takeover is strongly supported: this is the number in the first row, indicating an increase of about 0.03 to 0.04 percent in wages in response to each one percent increase in profits. These magnitudes seem small, but it must not be forgotten that profits are highly volatile, hence year on year increases in profitability reaching the double digits range are not uncommon, which would lead to significant changes in wages.

Table 2.6

	OLS(1)	OLS(2)	OLS(3)	FE(1)	FE(2)	FE(3)
Effect of profit in acquired firm	0.0424***	0.0408***	0.0273***	0.0388***	0.0388***	0.0353***
	(0.00363)	(0.00365)	(0.00340)	(0.00895)	(0.00897)	(0.00879)
Effect of profit in acquired firm after the merger	0.0195	0.0205	0.0191	0.0577	0.0596	0.0536
	(0.0169)	(0.0168)	(0.0153)	(0.0378)	(0.0399)	(0.0370)
Effect of profit in the parent firm after the merger	0.0708**	0.0649**	0.0692***	0.0843***	0.0841***	0.0844***
	(0.0283)	(0.0273)	(0.0244)	(0.0187)	(0.0188)	(0.0183)
Direct effect or merger	-0.117	-0.110	-0.110*	-0.234*	-0.239*	-0.177
	(0.0735)	(0.0721)	(0.0665)	(0.127)	(0.132)	(0.125)
Effect of K/L ratio		4.57e-05**			-5.01e-06	
		(2.07e-05)			(3.31e-05)	
Effect of % Skilled			0.394***			0.564***
			(0.0219)			(0.117)

Differently from the previous analysis, we test whether profit sharing changed over time, after the acquisition. The results in the second row which show rent sharing after the acquisition make clear that our hypothesis of a negative effect of takeover on the bargaining power of workers in the target firm is rejected. The estimated effect is indeed positive in all specifications, independently on the added covariate (here: capital intensity or share of skilled workforce of the firm). It is important to note that the estimated effect is also statistically insignificant: the standard errors or the estimates (which are reported below them between brackets) are of the same order of magnitude as the estimates themselves, and we can therefore not exclude that the effect is actually non-existent or even negative. The measurement is simply too imprecise to make strong statements about these effects. It seems that the takeover does not significantly change the workers' power of negotiation over the profits of the target firm with respect to the situation before the takeover. Our estimation, however, reveals that international profit sharing takes place in the Belgian setting after the acquisition, and that it is a more important contribution to wages than domestic profit sharing.

Our evidence also suggests that targets involved in acquisitions with companies in the same sector seem to enjoy higher rent sharing than firms which operate in a different sector as their acquirer, as far as the contribution of the target acquirer is concerned, but not with respect to their own rent sharing. This can be seen by adding the baseline estimated effect of rent-sharing which is given in the rows “effect of profit of acquired firm after merger” for domestic rent-sharing and “effect of profit of parent firm after merger” for international rent-sharing) with the effects below them, which indicate the additional effect solely for the set of firms indicated in the column name. The opposite applies for targets of “nested” acquisitions. This difference may reflect a number of issues besides statistical discrepancies. For example, it is possible that production process in the “nested” case is more complex for workers to understand, shifting bargaining power in favor of the employer. The workers will more likely extract a rent from the target company itself, which they know better than the acquirer. This would not apply to horizontal acquisitions, where the production process could be similar across countries.

The possibility for workers to understand the market of the acquirer and compare their situation with peers in the acquirer’s country may be driving the results in Table 2.7 below as well. International rent sharing is positive when the acquirer is based in one of Belgium neighboring countries, while it is slightly negative (but not significantly different from zero) when this is not the case. Coherently with Table 5, however, the cumulative acquirer rent sharing effect is positive, while the target one is not.

In the second part of Table 2.7 (columns 4 to 6) we investigate whether the degree of unionization in the country of the acquirer affects the propensity to rent sharing of the acquiring company. Intuitively, a tradition of strong unions in the acquirer’s country may increase the likelihood that management in the acquiring company extends the benefits of rent sharing to workers in the target company. Also, unions in the acquirer country may provide better information to workers in Belgium. This would be especially evident in the presence of international unions: Budd and Slaughter (2004) found evidence that international unions (between Canada and the U.S.) affect the degree of rent sharing in affiliates of companies whose headquarter is located abroad. In this spirit, international unions take into consideration the profit situation in one country to negotiate wages in the other country. We do not observe the degree of unionization of a single firm, nor that of the industry of the acquiring company. We therefore make use of the panel data on union density available from the OECD Statistics database (accessed: July 2014), and construct a dummy variable having value one if the acquirer’s country has a higher union density than the median of the countries in our database in a given year. We find that if the degree of unionization of the acquirer’s country is high, rent sharing is also higher.

Table 2.7

	Neighbouring country			**Unionization**		
	FE(1)	**FE(2)**	**FE(3)**	**FE(1)**	**FE(2)**	**FE(3)**
Effect of profit in acquired firm	0.0382***	0.0381***	0.0350***	0.0385***	0.0385***	0.0350***
	(0.0108)	(0.0108)	(0.0109)	(0.0111)	(0.0111)	(0.0113)
Effect of profit in acquired firm after the merger	-0.0282*	-0.0282*	-0.0269*	0.0596	0.0596	0.0603
	(0.0156)	(0.0156)	(0.0155)	(0.182)	(0.182)	(0.178)

Effect of profit in parent firm after the merger	-0.00531	-0.00531	-0.00454	0.00701	0.00753	0.00542
	(0.00472)	(0.00472)	(0.00458)	(0.0509)	(0.0505)	(0.0533)
Effect of profit in acquired firm, after merger, for parent firm from neighboring country / highly unionized country	0.0230	0.0227	0.0170	-0.0639	-0.0704	-0.0640
	(0.0751)	(0.0833)	(0.0735)	(0.222)	(0.237)	(0.217)
Effect of profit in parent firm, after merger, for parent firm from neighboring country / highly unionized country	0.205***	0.206***	0.200***	0.199***	0.199***	0.195**
	(0.0416)	(0.0429)	(0.0401)	(0.0753)	(0.0765)	(0.0763)
Direct effect of acquisition	0.0579	0.0580	0.0647*	-0.286	-0.288	-0.257
	(0.0405)	(0.0405)	(0.0389)	(0.496)	(0.495)	(0.486)
Direct effect of acquisition, considering the type of acquisition (nested or horizontal)	-0.554***	-0.553***	-0.470***	-0.217	-0.193	-0.185
	(0.128)	(0.148)	(0.123)	(0.575)	(0.627)	(0.562)
Effect of K/L ratio		7.84e-07			8.79e-06	
		(2.06e-05)			(3.84e-05)	
Effect of % Skilled			0.548***			0.554***
			(0.139)			(0.142)

3.4 Conclusions

In this section we presented evidence that both the acquired firms (by a foreign entity) and firms which were never acquired share profits with their workers in the form of wages. The takeover does not seem to affect significantly the rent sharing behavior of the target firm. On the other hand, after the acquisition, workers are able to appropriate part of the profits of the parent acquiring firm through higher wages. This result is robust to using a number of different methods of estimation, in which we take into account (i) industry linkages between acquirer and target firm, (ii) the location of the acquirer, its union density, and its skill intensity, (iii) other definitions of profits, controls and the percentage of shares purchased in the deal.

4. Measuring firm-level phenomena with firm-level data

The increasing availability of firm-level matched employer-employee data facilitated the emergence of an alternative approach to measuring discrimination with individual-level data. One of the first papers that combined the productivity and labour cost dimensions was that of Hellerstein et al. (1999). In a recent replication of that seminal analysis using data covering the US manufacturing sector, the authors (Hellerstein & Neumark, 2007) estimate relative productivity of workers aged 55+ is only 0.87 (ref. group <35 =1), whereas relative wages is 1.12. Most papers based on cross-sectional data conclude that firm productivity has an inverted U-shaped relationship with age, while labour costs are either rising with age or flat beyond a certain threshold with a negative impact on the productivity-labour cost ratio after 55 (Grund & Westergård-Nielsen, 2008; Skirbekk, 2004, 2008).

Our point is that none of the existing papers has adequately considered the gender dimension of ageing, in a context where women are likely to form a growing part of the older labour force. This chapter aims at filling that void. We try to assess the current willingness of employers to (re)employ older male and female workers. And we posit that the answer to this question largely depends on how larger shares of older (male or female) workers affect private firms' productivity-labour cost ratio. We assume in particular that a sizeable negative impact of older men/women on that ratio can adversely affect their respective chances of being employed.

Using panel data and coping with the endogeneity of the age structure of the workforce has become key in this literature/ Another key distinction in terms of methodology is between studies which only examine productivity and those that simultaneously consider pay or labour costs. Economists with a focus on labour demand assess employability by examining the ratio of (or the gap between) individuals' productivity to (and) their cost to employers.

The basic Hellerstein-Neumark model is based on the separate estimation of an added-value function and a wage equation at the firm level. The added-value function yields estimates for the average marginal product of each category of workers (part-time workers, women, etc), while the wage equation estimates the respective impact of each group on the average wage paid by the firm. Estimating both equations with the same set of explanatory variables allows comparing the parameters regarding the (average) marginal product and the (average) wage. This technique was developed in Hellerstein et al. (1999; 2004) and refined by Aubert and Crépon (2003) and van Ours and Stoeldraijer (2011). It is now standard in the literature regarding the productivity and wage effects of labour heterogeneity (Cataldi et al. 2012; Göbel and Zwick 2012).

Under proper assumptions, this amounts to analysing the sensitivity of the productivity-labour cost ratio to the employment structure of firms (see Box 1).

Box 2.1- The Hellerstein-Neumark Methodology

Most of the results present in this report rest on the Hellerstein-Neumark approach to labour heterogeneity. To estimate productivity (and/or wage) profiles according to a given characteristic of the workforce (e.g; age, gender or education attainment, following most authors in this area, we consider a Cobb-Douglas technology (Hellerstein *et al.*, 1999; Aubert & Crépon, 2003, 2007; Dostie, 2011; van Ours & Stoeldraijer, 2011; Vandenberghe, 2011a,b):

$lnY_{it}=lnA + \alpha\ ln\ QL_{it} + ß\ lnK_{it}$ [1.]

where: Y_{it} /L_{it} is the average value added per worker (average productivity hereafter) in firm i at time t, QL_{it} is an aggregation of different types of workers, and K_{it} is the stock of capital.

The variable that reflects the heterogeneity of the workforce is *the quality of labour index* QL_{it}. Let L_{ijt} be the number of workers of type j (*e.g.* young /old; men/women; low/high educated) in firm i at time t, and μ_{ij} be their contribution to output. We assume that workers of various types are substitutable with different marginal products. As each type of worker j is assumed to be an input in quality of labour aggregate, the latter can be specified as:

$QL_{it} = \sum_j \mu_{ij}\ L_{ijt} = \mu_{i0}\ L_{it} + \sum_{j>0} (\mu_{ij} - \mu_{i0})\ L_{ijt}$ [2.]

where: $L_{it} \equiv \sum_j L_{ijt}$ is the total number of workers in the firm, μ_{i0} the marginal productivity of the reference category of workers (*e.g.* prime-age men) and μ_{ij} that of the other types of workers.

If we further assume that a worker has the same marginal product across firms, we can drop subscript i from the marginal productivity coefficients. After taking logarithms and doing some rearrangements equation (2) becomes:

$ln\ QL_{it} = ln\ \mu_0 + lnL_{it} + ln\ (1+ \sum_{j>0} (\lambda_j\ - 1)\ S_{ijt})$ [3.]

where $\lambda_k \equiv \mu_k/\mu_0$ is the relative marginal productivity of type k worker and $S_{ijt} \equiv L_{ijt}/L_{it}$ the share of type j workers over the total number of workers in firm i .

Since $ln(1+x) \approx x$, we can approximate [3] by:

$ln\ QL_{it} = ln\ \mu_0 + ln\ L_{it} + \sum_{j>0} (\lambda_k\ - 1)\ S_{jt}$[4.]

And the production function becomes:

$lnY_{it}=lnA+ \alpha\ [ln\mu_0 + ln\ L_{it} + \sum_{j>0} (\lambda_j-1)\ S_{ijt}] + ß\ lnK_{it} - lnL_{ik}$ [5.]

Or, equivalently, if $j=0,1,\ldots.N$ with $j=0$ being the reference group (*e.g.* prime-age male workers)

$y_{it} = B + \alpha l_{it} + \eta_1\ S_{i1t} + \ldots\ \eta_N\ S_{iNt} + ß\ k_{it}$ [6.]

where:

$B=lnA+\alpha\ ln\ \mu_0\ ;\ \lambda_j=\mu_j/\mu_0$ $j-=1\ldots N$

$\eta_1 = \alpha\ (\lambda_1\ - 1)\ \ldots.\ \eta_N = \alpha\ (\lambda_N - 1)$

$y_{it}=lnY_{it};\ l_{it}=lnL_{it};\ k_{it}=lnK_{it}$

Note first that [6], being loglinear in S, has coefficients can be directly interpreted as the percentage change in the firm's average labour productivity of a 1 unit (here 100 percentage points) change of the considered type of workers' share among the employees of the firm. Note also that, strictly speaking, in order to obtain a type j worker's relative marginal productivity, (*i.e.* λ_j), coefficients η_j have to be divided by α, and 1 needs to be added to the result.[2]

A similar approach can be applied to a firm's average labour cost leading to a very similar equation

$w_{it}=B^w+\alpha^W l_{it} +\eta^W{}_1\ S_{ij1t}+\ldots+ \eta^W{}_N\ S_{iN\,t} +ß^w\ k_{it}$ [7.]

[2] Does all this matter in practice? Our experience with firm-level data suggests values for $ß$ ranging from 0.6 to 0.8 (these values are in line with what most authors estimates for the share of labour in firms' output/added valye). This means that λ_k are larger (in absolute value) than η_k. If anything, estimates reported in Tables b 6 underestimate the true marginal productivity difference vis-à-vis prime-age workers.

The key hypothesis test can now be easily formulated. Assuming spot labour markets and cost-minimizing firms the null hypothesis of no impact on the productivity-labour cost ratio for type *k* worker implies $\eta_J = \eta^w{}_J$ Any negative (or positive) difference between these two coefficients is a measure of the degree of misalignement of relative marginal productivity and labour cost. It will be interpreted by labour economists interrested in labour deamdn as a quantitative measure of the disincentive (incentive) to employ the category of workers considered (e.g. older female worker). It can also can be interpreted as evidence of positive(negative) wage discrimination between the categories of workers considered (e.g. men vs women).

Note that the above test that can easily implemented if one adopts strictly equivalent econometric specifications for the average productivity and average labour cost; in particular if we introduce firm size (l) and capital stock (k) in the labour cost equation [7]. The most straighforward way is to take the *difference* between the logarithms of average productivity [6] and labour costs[3] [7] we get a direct expression of the productivity-labour cost ratio[4] as a linear function of its workforce determinants.

$Ratio_{it} \equiv y_{it} - w_{it} = B^R + \alpha^R l_{it} + \eta^R{}_1\, S_{ij\,t} + \ldots + \eta^R{}_N\, S_{iN\,t} + \beta^R\, k_{it}$ [8.]

where: $B^R = B - B^w;\ \alpha^R = \alpha - \alpha^W,\ \eta^R{}_1 = \eta_1 - \eta^w{}_1 \ldots \eta^R{}_N = \eta_N - \eta^w{}_N;\ \gamma^R = \gamma - \gamma^w$ and $\varepsilon^R{}_{it} = \varepsilon_{it} - \varepsilon^w{}_{it}$.

It is immediate to see that coefficients $\eta^R{}_j$ of equation [8] provide a direct estimate of the degree of alignement of the productivity and labour cost for type *j* workers.

There are two main advantages of the approach we adopted over competing methodologies. First, it provides a direct measure of gender productivity differences that can be subsequently compared to a measure of gender labour costs differences, thereby identifying gender wage discrimination. Second, it measures, and tests for the presence of, a concept of market-wide gender wage discrimination. Hellerstein & Neumark's methodology has also been used to test other wage formation theories, most notably those investigating the relationship between wages and productivity along age profiles, e.g. Hellerstein & Neumark (1995). Extensions of the basic methodology include enlarging the scope of workers characteristics, such as age, race and marital status, e.g. Hellerstein et al. (1999) or Vandenberghe & Waltenberg (2010); Vandenberghe (2011a,b), Vandenberghe (2012), and the consideration of richer data sets regarding employee information, e.g. Crépon, Deniau & Pérez-Duarte (2002). In this chapter, we will focus on gender and also the interaction between gender and the worker's blue- vs. white-collar status.[5]

5. Overview of different statistical estimators used by EDIPO research

Firm-level productivity and wage equations can be estimated with different methods: pooled ordinary least squares (OLS), a fixed-effect (FE) model, the generalized method of moments (GMM) estimator proposed by Arellano and Bover (1995) and Blundell and Bond (1998), or a more structural approach suggested by Levinsohn and Petrin (2003, hereafter LP).

This being said, pooled OLS estimators of productivity models have been criticized for their potential "heterogeneity bias" (Aubert and Crépon 2003: 116) due to the fact that firm productivity depends to a large extent on firm-specific, time-invariant characteristics that are not measured in

[3] Labour costs used in this paper, which were measured independently of value added, include the value of all monetary compensations paid to the total labour force (both full- and part-time, permanent and temporary), including social security contributions paid by the employers, throughout the year. The summary statistics of the variables in the data set are presented in Table b1.

[4] Measured in %. This is because the logarithms, used in conjunction with differencing, convert absolute differences into relative (i.e., percentage) differences: i.e. *(Y-W)/W.*

[5] Historically in Belgium, white collars (or "employees") were those performing work that requires predominantly mental rather than physical effort (presumably educated people thus), whereas the blue collars (or "workmen") were employed in manual/ unskilled labour. But that distinction has partially lost its relevance, particularly for the white-collar group that now encompasses a rather heterogeneous set of activities and levels of education). The distinction also largely recoups separate industrial relation arrangements (different rights and obligations in terms of notice period, access to unemployment insurance benefits…).

micro-level surveys (advantageous location, firm-specific assets like the ownership of a patent, or other firm idiosyncrasies).

One way to remove unobserved firm characteristics that remain unchanged during the observation period is by estimating a FE model. Empirical studies have shown that firm-level fixed-effects are important for the wage differentials between male immigrants and male natives and attenuate the problem of unobserved firm characteristics (Aydemir and Skuterud 2008), but the fixed-effect estimator does not address the potential endogeneity of the explanatory variables. Indeed, neither pooled OLS nor the FE estimator address the potential endogeneity of our explanatory variables.[6]

Yet, labour diversity is likely to be endogenous. Indeed, any shock in wages or in productivity levels might generate correlated changes in the firm's workforce and in labour productivity that are not due to changes in the firm's workforce composition per se. For instance, one might expect that a firm undergoing a negative productivity shock would prefer not to hire new staff, which would increase the age of the workforce and affect the age diversity index. Similarly, during economic downturns, firms may be more likely to reduce personnel among women and less educated workers as adjustments costs are often lower for these categories of workers due to their relatively lower wages and/or tenure. In order to control for this endogeneity and for the presence of firm fixed effects, we estimated our model using system GMM (GMM-SYS) and LP estimators, respectively.

The GMM-SYS approach boils down to simultaneously estimating a system of two equations (one in level and one in first differences) and to relying on internal instruments to control for endogeneity. More precisely, diversity variables in the differenced equation are instrumented by their lagged levels and diversity variables in the level equation are instrumented by their lagged differences (Göbel and Zwick, 2012). The implicit assumption is that changes (the level) in (of) the dependent variable – productivity or wages – in one period, although possibly correlated with contemporaneous variations (levels) in (of) diversity variables, are uncorrelated with lagged levels (differences) of the latter. Moreover, changes (levels) in (of) diversity variables are assumed to be reasonably correlated to their past levels (changes). One advantage of GMM-SYS is that time-invariant explanatory variables can be included among the regressors, while the latter typically disappear in difference GMM. Asymptotically, the inclusion of these variables does not affect the estimates of the other regressors because instruments in the level equation (i.e. lagged differences of diversity variables) are expected to be orthogonal to all time-invariant variables (Roodman, 2009). In order to find the correctly specified model, we start with the moment conditions that require less assumptions and increase the number of instruments progressively (Göbel and Zwick, 2012). To examine the validity of additional instruments, we apply the Hansen (1982) test of over-identifying restrictions. In addition, Arellano-Bond (1991) test for serial correlation (i.e. for second-order autocorrelation in the first differenced errors) is used to assess whether estimates are reliable. Practically, we choose the model with the lowest number of lags that passes the Hansen and Arellano-Bond tests.

As an alternative to the GMM-SYS method, Olley and Pakes (1996) have developed a consistent semi-parametric estimator. This estimator, particularly well suited for panels with small t and big N, controls for endogeneity and firm fixed unobserved heterogeneity by using the employer's investment decision to proxy for unobserved productivity shocks. The intuition is that firms respond to time-varying productivity shocks observed by managers (and not by econometricians) through the adjustment of their investments. Put differently, profit-maximizing firms react to positive/negative productivity shocks by increasing/decreasing their output, which requires more/less investments (or intermediate inputs, see below). The OP estimation algorithm relies on the assumptions that there is only one unobserved state variable at the firm level (i.e. its

[6] Expected biases associated to OLS and the relatively poor performance and shortcomings of the FE estimator in the context of firm-level productivity regressions are reviewed in Van Beveren (2010).

productivity) and that investments increase strictly with productivity (conditional on the values of all state variables). This monotonicity condition implies that any observation with zero investment has to be dropped from the data, which generally leads to a sharp decrease in sample size. To avoid this drawback, Levinsohn and Petrin (2003) use intermediate inputs (i.e. inputs such as energy, raw materials, semi-finished goods, and services that are typically subtracted from gross output to obtain added value) rather than investments as a proxy for productivity shocks. Given that firms typically report positive values for intermediate inputs in each year, most observations can be kept with the LP approach. An additional argument for using intermediate inputs rather than investments is that the former may adjust more smoothly to the productivity term than the latter, especially if adjustment costs are an important issue. For instance, "if adjustment costs lead to kink points in the investment demand function, plants may not respond fully to productivity shocks, and some correlation between the regressors and the error term can remain" (Petrin et al., 2004: 114). Intermediate inputs would thus provide a better proxy for unobserved productivity shocks. In the basic LP model, labour is a fully variable and capital a fixed input. Given our focus on diversity, the variable inputs in our setup include first and/or second moments of workforce characteristics. Assuming that intermediate inputs depend on capital and the unobservable productivity shocks, this relationship can be solved for the productivity term (Ilmakunnas and Ilmakunnas, 2011). When relying on the LP estimation algorithm, standard errors are computed using a bootstrap approach taking the panel structure of the data into account (Petrin et al., 2004).

There is a range of statistical tests designed to assess the soundness of the chosen estimator. For the case of GMM-SYS estimators, the first test measures whether the correlation between the instrumental variables and the endogenous variables is sufficiently strong, i.e. that the instruments are not 'weak'. For this purpose we used the Kleibergen-Paap rk Wald F statistic. Under the null hypothesis the instruments are weak. A standard rule of thumb is to reject the null hypothesis if the F-statistic is at least 10 (Van Ours and Stoeldraijer 2011). The second test is the Kleibergen-Paap rk LM statistic, whose null hypothesis is that the equation is underidentified. The third test concerns the validity of the instruments and uses the Hansen (1982) test of overidentifying restrictions. Under the null hypothesis the instruments are valid, i.e. uncorrelated with the error term. A fourth indicator tests whether the immigrant shares are indeed endogenous so that an IV approach is warranted. Under the null hypothesis the explanatory variables can actually be treated as exogenous.

Box 2.2- Econometric identification

From the econometric standpoint, recent developments of HN's methodology have tried to improve the estimation of the production function by the adoption of alternative techniques to deal with a potential heterogeneity bias (unobserved time-invariant determinants of firms' productivity that are correlated with labour inputs) and simultaneity bias (endogeneity in input choices in the short run that includes firm's age-gender mix). A standard solution to the heterogeneity bias is to resort to fixed-effect analysis, generally via first-differencing (FD) of panel data.

As to the endogeneity bias, the past 15 years has seen the introduction of new identification techniques.7 One set of techniques follows the dynamic panel literature (Arellano & Bond, 1991; Aubert & Crépon, 2003; Blundell & Bond, 2000; or van Ours & Stoeldraijer, 2011), which basically consists of using lagged values of (first-differenced) labour inputs as instrumental variables (FD-IV-GMM henceforth). A second set of techniques, initially advocated by Olley & Pakes (1996), Levinsohn & Petrin (2003) (OP, LP henceforth), and more recently by Ackerberg, Caves & Fraser (2006) (ACF henceforth), are somewhat more structural in nature. They consist of using observed intermediate input decisions (i.e. purchases of raw materials, services, electricity…) to "control" for (or proxy) unobserved short-term productivity shocks.

7 See Ackerberg, Caves & Frazer (2006) for a recent review.

Thoughout the research presented here we use these recent applications of the HN methodology that we apply to panel data that have been first differenced (FD), in order to account for time-invariant unobserved heterogeneity. We also apply two strategies that are aimed at coping with endogeneity/simultaneity. Following many authors in this area (Aubert & Crépon, 2003, 2007; van Ours & Stoeldraijer, 2011; Cataldi, Kampelmann & Rycx, 2011), we first estimate the relevant parameters of our model using FD "internal" instruments (i.e lagged values of endogenous labour inputs) (FD-IV-GMM henceforth). Second, we also implement the more structural approach initiated by Olley & Pakes (1998), further developed by Levinsohn & Petrin (2003) and more recently by Ackerberg, Caves & Frazer (2006) (ACF hereafter), which primarily consists of using intermediate inputs to control for short-term simultaneity bias. Note that we innovate within this stream, as we combine the ACF intermediate-good approach with FD, to better account for simultaneity and firm heterogeneity (FD-ACF henceforth).

PART II – At-risk group: women

CHAPTER 3 - Gender wage discrimination in the Belgian private economy

Groups displaying poor labour-market outcomes could be discriminated. Evidence of substantial average earning differences between men and women — what is often termed the gender wage gap — is a systematic and persistent social outcome in the labour markets of most developed economies. Commonly, people refer to wage discrimination as the wage differential between members of a minority group (women/immigrant) and the majority group (men/natives), and that manifests itself by a lower pay. Strictly speaking however, from an economic point of view, wage *discrimination* requires more than wage differences between groups. It implies that equal labour services provided by equally productive workers have a sustained price/wage difference.

The standard empirical approach among economists to the measurement of wage discrimination consists of estimating earning/wage equations and applying Oaxaca (1973) and Blinder (1973) decomposition methods. But what is almost invariably missing from the Oaxaca-Blinder studies is an independent and reliable measure of productivity. By contrast, in this part of the research we intend to use firm-level direct measures of productivity and wage differentials. Under proper assumptions the comparison of these two estimates provides a direct test for wage discrimination. One advantage of this setting it that it avoids identifying as discrimination wage differences that can be ascribed to productivity differences.

Evidence of substantial average earning differences between men and women— what is often termed the gender pay gap — is a systematic and persistent social outcome in the labour markets of most developed economies. This social outcome is often perceived as inequitable by a large section of the population and it is generally agreed that its causes are complex, difficult to disentangle and controversial (Cain, 1986). In 1999, the gross pay gap between women and men in the EU-27 was, on average, 16% (European Commission, 2007), while in the U.S. this figure amounted to 23.5% (Blau and Kahn, 2000). Belgian statistics (Institut pour l'égalité des Femmes et des Hommes, 2006) suggest gross monthly gender wage gaps ranging from 30% for white-collar workers to 21% for blue-collar workers.

Although historically decreasing the gender pay gap, and particularly the objective of further reducing its magnitude, remains a central political objective in governments' agendas both in Europe and in the U.S. The gender pay gap provides a measure of what Cain (1986) considers the practical definition of gender discrimination. In Cain's conceptual framework gender discrimination, as measured by the gender pay gap, is an observed and quantified outcome that concerns individual members of a minority group, women, and that manifests itself by a lower pay with respect to the majority group, men.

In this chapter we measure, and test for, the presence of gender wage discrimination (as traditionally defined by economists) in the Belgian labour market by employing a methodological approach, pioneered by Hellerstein & Neumark (1995), using a large data set that matches firm-level data, retrieved from Belfirst, with data from Belgian's Social Security register containing detailed information about the characteristics of the employees in those firms.

Our preferred estimates indicate that the cost of employing women is 6 percentage points lower than that of men, pointing at a wage differential of similar magnitude. But on average, women's collective contribution to a firm's value added (or productivity) is estimated to be about 6 to 12 percentage points lower than that the group of male workers. The key result of the chapter, however, is that *we cannot not reject the hypothesis that the estimated gender labour costs/wage differential is equal to the estimated gender productivity differential*. Our implementation of a Wald test of equality does not lead us to reject the null hypothesis of equality between these two differentials. The tentative conclusion is that, for private for-profit firms based in Belgium, productivity differences between male and female workers fully account for labour costs differences.

Our labour cost estimates are consistent with evidence obtained in previous studies of the gender pay gap in the Belgian labour market (Meulders & Sissoko, 2002), in the sense that they systematically point at lower pay for women. But our work adds new results to previous evidence for two reasons mainly. First, because we use firm-level data we are also able to estimate gender productivity differences and show that firm employing more women tend to generate less value added *ceteris paribus*. Second, by estimating labour costs and productivity equations simultaneously we are able to show that there is no statistically significant *gap* between the gender labour cost differential and the gender productivity differential: something that we interpret at the absence of wage discrimination.

The rest of this chapter is organised in the following way. Section c.1 describes the data and presents summary statistics. In Section c.2 we present, discuss and interpret the results of our preferred econometric specifications. Section c.3 summarizes and concludes our analysis.

1. Data and descriptive statistics

The firm-level data we use in this chapter involves input and output variables of close to 9,000 firms of the Belgian private economy observed along the period 1998-2006. The data set matches financial and operational information retrieved from Belfirst with data on individual characteristics of all employees working in the firms, obtained from the Belgium's Social Security register (the so-called Carrefour database). The data set covers all sectors in the Belgian non-farming private economy, identified by NACE2 code[6]. Monetary values are expressed in nominal terms.

The productivity outcome corresponds to the firms' net value added: the value of output less the values of both intermediate consumption and consumption of fixed capital. The measure of labour costs, which was measured independently of net-value added (Figure c.1), includes the value of all monetary compensations paid to the total labour force (both full- and part-time, permanent and temporary), including social security contributions paid by the employers, throughout the year. The summary statistics of the variables in the data set are presented in Table c.1 and Table c.2.

Table 3.1: Belfirst-Carrefour panel. Basic descriptive statistics. Mean (Standard deviation in italics).

Year	Nobs	Net value-add (th.€)	Labour costs (th.€)	Number of employees	Capital (th.€)	Average hours worked[a]	Share of female	Share of blue-collar female	Share of blue-collar male	Share of white-collar female	Share of white-collar male
1998	7584	7,760	4,800	108	6,388	1576	0.263	0.085	0.486	0.177	0.251
		50,301	32,805	474	99,443	502	0.245	0.168	0.341	0.205	0.231
1999	7743	8,192	5,017	111	6,548	1576	0.266	0.085	0.482	0.180	0.252
		54,668	32,455	475	103,365	310	0.244	0.167	0.340	0.205	0.229
2000	7929	8,837	5,314	114	6,857	1566	0.271	0.085	0.475	0.185	0.254
		55,296	32,539	472	111,964	324	0.244	0.166	0.339	0.207	0.228
2001	8121	9,027	5,646	121	7,477	1574	0.274	0.084	0.468	0.189	0.258
		53,836	32,959	511	119,272	883	0.244	0.164	0.339	0.209	0.228
2002	8262	9,565	6,172	128	8,043	1544	0.275	0.082	0.462	0.192	0.263
		59,781	39,160	690	130,471	343	0.243	0.162	0.339	0.210	0.230
2003	8353	10,128	6,384	127	8,508	1531	0.276	0.082	0.459	0.194	0.265
		58,778	37,988	643	138,520	301	0.243	0.161	0.339	0.211	0.230
2004	8355	10,954	6,667	129	8,870	1542	0.276	0.081	0.456	0.194	0.268
		63,694	37,649	644	147,481	246	0.242	0.161	0.338	0.210	0.230
2005	8338	11,438	6,912	132	8,052	1525	0.276	0.080	0.454	0.196	0.270
		64,558	37,691	645	62,724	276	0.242	0.159	0.338	0.210	0.230
2006	8261	12,367	7,311	134	8,250	1517	0.280	0.080	0.448	0.200	0.272
		68,878	39,686	638	61,954	1666	0.242	0.158	0.336	0.212	0.230

a: Total number of hours worked during the year divided by the total number of employee (full-time or part-time ones).

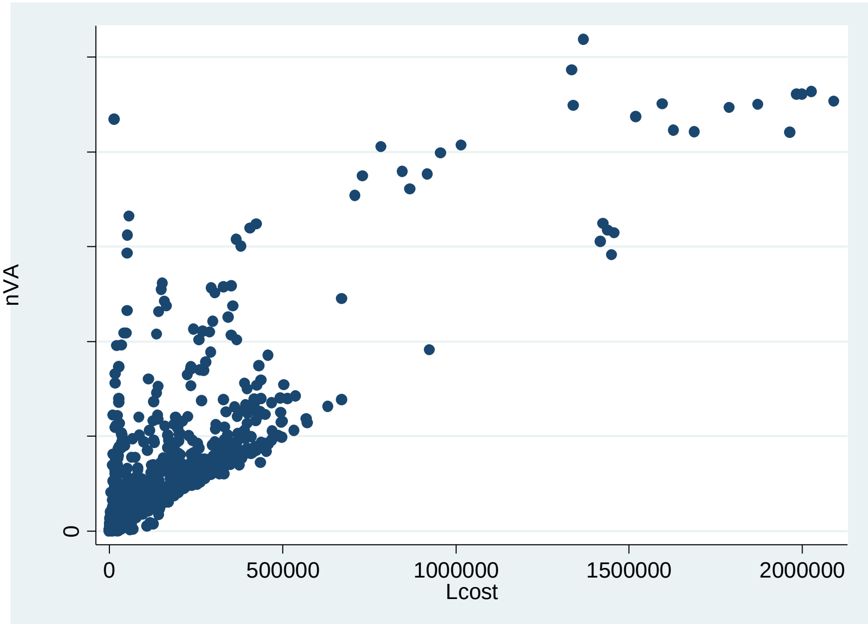
Table .3.2: Belfirst-Carrefour panel. Basic descriptive statistics, pooled data

Firm size	**Nobs**
1-49	44354
50-99	14664
100+	13928
Region	
Brussels	10722
Vlaanderen	46008
Wallonia	16216

The Figure below shows an expected pattern: a positive relation between firms' net value added (our measure of output) and their labour costs, with an overwhelming majority of firms reporting lower labour costs than their net value added. The Figure reveals that productivity variance is higher than labour costs variance. It its lower panel, it also suggests that both average labour costs and productivity decline with the (rising) share of women employed by a firm.

Finally, intermediate inputs pay a key role in our analysis, as they are central to our strategy to overcome the simultaneity bias. It is calculated here as the differences between the firm's turnover (in nominal terms) and its net value-added. It reflects the value of goods and services consumed or used up as inputs in production by enterprises, including raw materials, services and various other operating expenses.

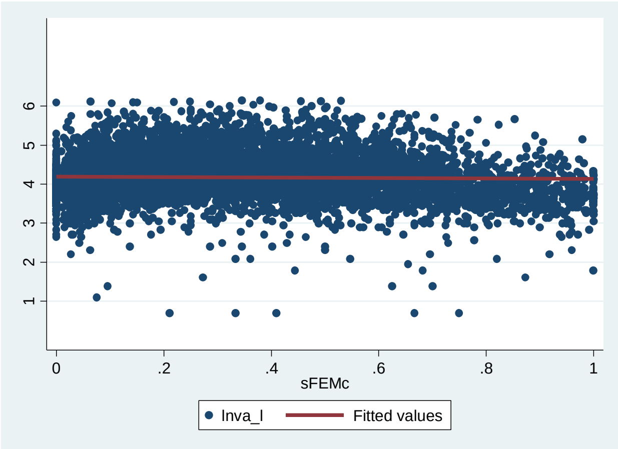
Figure 3.1: Firms' labour costs versus firms' net value added (in th. €), pooled data



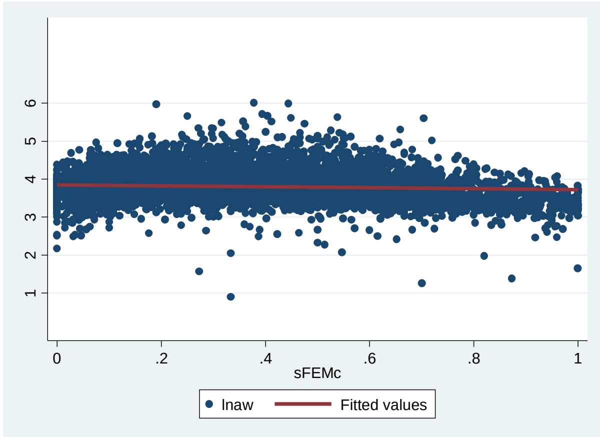
Source: Carrefour, Belfirst

Figure 3.3: Share of women in firms' workforce (on the horizontal axis) versus firms'

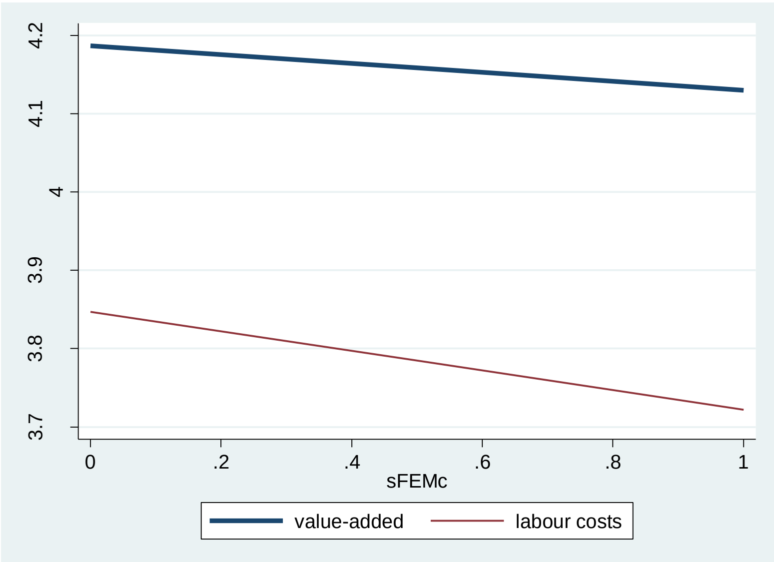
Log value-added per employee (scatter & fit)



Log labour costs per employee (scatter & fit)



Log value-added per employee vs log labour costs per employee (fit)



Source: Carrefour, Belfirst

2. Econometric Analysis

This section starts by complementing the description and justification of our methodological choices exposed in generic terms in Box 1; next, it analyses the results of our estimations and, finally, interprets the results in light of existing gender economic discrimination theories and previous evidence for the Belgian labour market.

In Table 3.3 we present results of the independent estimation of production and the labour costs equations under six alternative econometric specifications: standard OLS using total variance [1] then OLS using only between-firm (or cross-sectional) variance [2]. Then comes the LP intermediate consumption “proxy” using total variance [3]. The next model uses first-differenced variables [4]. The fifth model is the within model (where each observation has been centred of the firm average over the duration of the panel). Finally, our preferred model is the one that combines the HP idea and the within-firm model [6].

Further ahead, in Table 3.4, we will focus on the simultaneous estimation of the production and labour costs functions using our preferred model [6] with the aim of assessing the statistical significance of the gap between gender productivity vs. labour costs differentials.

Specification [6] in Table 3.4 is a priori the best insofar as the coefficients of interest are identified from within-firm variation and that it controls for potential heterogeneity and simultaneity biases using LP’s intermediate input proxy strategy. Heterogeneity bias might be present since our sample covers all sectors of the Belgian private economy and the list of controls included in our models is limited. Even if the introduction of the set of dummies can account for most of this bias, the «within firm» transformation [5], [6] (or the first-differing one [4]) are still the most powerful way to account of inter-firm unobserved heterogeneity.

Despite the considerations we made in the previous paragraphs, we believe specifications [1] to [4] provide valuable information about the presence and magnitude of biases, so that we will draw tentative evidence from comparison of the results of the alternative specifications.

We now make a final a justification for our preferred joint estimations of production and labour cost equations (Table 3.4). We recall that the focus of our analysis is the implementation of the gender wage discrimination test, which involves testing the equality of estimates of productivity (η) and labour costs (η^W) differentials, obtained from estimations of the production function and the labour costs equations. Options here are essentially twofold.

First, joint estimation of the two equations (using *e.g.* the *SUREG*, Stata command). We recall that the arguments for joint estimation — what corresponds to *system FGLS* estimation in Wooldridge (2002)’s terminology — are essentially two. One is that joint estimation provides a direct way to implement a Wald test of the equality of a non-linear combination of coefficients across equations. If there are unobservables in both equations that bias the estimates of η and η^W as long as they affect the two equations equally, which should occur under the null, their effect on the Wald equality test is neutralized. Another is that joint estimation makes use of cross-equation correlations in the errors, thereby increasing the efficiency (i.e. generate smaller standard errors) of the coefficient estimates.Alternatively, one can perform so-called *system OLS* estimation. This consists of estimating the two equations separately, but to use those estimates to construct a cluster-adjusted robust sandwich variance-covariance matrix, which can be used to perform a Wald test of equality of the two coefficients.

The choice between system OLS and system FGLS can be viewed as a trade-off between robustness and efficiency. On the one hand, system OLS is more robust (i.e. generate coefficient that are less likely to be biased). It is consistent under the milder assumption of contemporaneous exogeneity, while the consistency of system FGLS is conditional on strict exogeneity of the regressors. Moreover, the Wald test computed from system OLS estimation can be made robust to arbitrary heteroskedasticity and serial correlation in the error term, while system FGLS does so under the assumption of system homoskedasticity. In principle, we could construct a cluster-adjusted robust sandwich variance-covariance matrix from the FGLS estimates. However, the Stata command that implements FGLS, *SUREG*, does not permit its computation from standard commands. On the other hand, system FGLS takes advantage of increased efficiency from cross-equation correlations in the errors.

We decided to implement *system OLS* in addition to the more common *system FGLS* (used for instance by Hellerstein & Neumark (1995) and Hellerstein *et al.* (1999) for four reasons. First, because we are using panel data, so that the error term should normally be serially correlated for the same firm, the ability to control for arbitrary heteroskedasticity and serial correlation across time is a strong advantage. Second, the advantage of controlling for potential unobservables is substantially smaller in our case: while Hellerstein & Neumark (1995) and Hellerstein *et al.* (1999) used cross section data and implemented standard OLS and IV estimators, instead, we use panel data and implement estimation procedures specifically designed to deal with potential biases due to unobservables. Third, the importance of cross-equation correlation in the errors needs to be assessed vis-à-vis the efficiency of the estimates obtained from independent estimations. In our case, the precision of coefficient estimates using system OLS is fairly satisfactory. Fourth and last, the assumption of strict exogeneity is very strong for production function estimation. That said, the efficiency gains associated with system FGLS seem to be high for our data set: the cross-equation correlation of the residuals is high both for the raw and the transformed data, respectively 69%, for total-firm variation, and 56% for within-firm variation, and 60%, for total-firm variation, and 40% for within-firm variation.

Table 3.3 displays the parameter estimates of the production and labour costs functions when these are estimated separately.

The lower part of Table 3.3 contains the estimates of the gender productivity (η) and labour costs (η^W) differentials. Estimated ηpoint at lower productivity inside firms employing more women. Male to female productivity differentials range for 0 to -18 percentage points. Those for η^W are significant and point negative labour costs differentials for women. These range from 0 to -17 percentage points.

The crucial issue, however, is the gap between these gender differentials as it captures the intensity of gender wage discrimination. We report different estimates of this gap on the bottom line of Table 3.3 OLS estimates (column [1]) suggest that women in the Belgian labour market are paid 12 percentage point less than what their (relative) productivity would imply. Turning to the between-firm estimates (were we solely use the between firm variance), we get an even larger gap of 13 percentage points. But focusing on the within-firm variance (in order to account for time-invariant unobserved heterogeneity) considerably reduces that gap. Indeed, estimates reported in column [5] translate into a now negative gap of about 3 percentage points. And when we combine the within approach (to control for time-invariant heterogeneity) and the LP's proxy strategy to control for short-term endogeneity, we get a negative gap of 6 percentage points. In other words, the gender labour costs differential is smaller than the productivity differential. Although these results require further qualifications (more on this below), they suggest that most of the evidence in support of gender pay discrimination vanishes once cross-firm unobserved heterogeneity and simultaneity bias have been controlled for.

The dramatic reduction of the differential gap when moving from total- to within-firm variance constitutes important evidence in support of controlling for cross-firm heterogeneity and rejecting OLS [1], between [2] on LP-only [3] estimates. This is particularly true for the labour costs equation. The within-firm labour costs differential is much smaller (6 percentage points [5], [6]) than in previous models (17 percentage points with OLS [1] see lower part of Table 3.3).

The different estimates of the productivity differentials are also affected by the within transformation, although to a lesser extent than labour cost differentials. Controlling for unobserved heterogeneity and simultaneity bias combining within and LP [6] leads to gender productivity differentials of greater magnitude (-5 percentage points with OLS [1] vs. -13 percentage points with our preferred estimate [6], see lower part of Table 3.3).

The latter results accords with our initial prediction. Based on evidence for the Belgian labour market summarized in Meulders & Sissoko (2002), we were convinced that, if anything, the presence of simultaneity bias would lead to an underestimation of the gender productivity differential in OLS estimations. Our reasoning was the following: since in Belgium temporary contract employment is asymmetrically concentrated in female employment, we should expect that, if temporary employment is one, or the main, labour adjustment variable to shocks in firms economic environments, the share of female employment should increase in periods of positive productivity shocks and decrease in periods of negative productivity shocks. This would generate positive correlation between the share of female labour force and the productivity of firms, thereby leading to underestimated OLS estimates of the gender productivity differential. As we have just argued our results do confirm this prediction.

But strictly speaking, we cannot conclude to the absence of gender discrimination without properly *testing* for the equality of the gender productivity (η) and labour costs differentials (η^W) . Table 3.4 presents estimates of η and η^W obtained from both system FGLS and system OLS estimations of the production function and the labour costs equation, and the p-values of Wald equality tests of these coefficients.

With system FGLS, the estimates of η and η^W (and the resulting gaps) are approximately the same as those obtained from system OLS estimates (Table 3.4) and, as expected, the precision of the estimates increased slightly owing to the high correlation in the residuals across equations (around 60% for total-firm estimations and around 40%, for within-firm estimations). But in both cases high p-values of the Wald equality tests statistic (0.84 and 0.28 respectively) lead to the acceptance of the null hypothesis of no gender wage discrimination.

We have undertaken two further steps in our analysis to assess the robustness of these results. First, we have examined whether our results change much when we partition the sample in terms of *firm size*. Second, we go beyond the simple distinction between men and women and consider *the interaction of status* (blue-collar/white collar) *and gender*. Referring to equations 6 and 9, this means estimating these models with k=0,1,2,3 categories of workers, where the reference category in our case (k=0) are the blue-collar men. Note in particular that the white vs. blue-collar workers comparison is a way to somehow compensate for the lack of information on the level of education (which is one shortcoming of our data). For each of these extensions, the focus will be on the results of the model with intermediate inputs *à-la*-LP with firm fixed effects (exploiting within-firm variance). We also resort to both system FGLS (Table 3.5, panel A) and system OLS (Table 3.5, panel B) to assess the null hypothesis of no gender wage discrimination ($\eta = \eta^W$).

The main results from these breakdowns do not differ in qualitative terms from those obtained using the overall sample. Whatever the method used (system FGLS or system OLS), we conclude to the absence of systematic gender discrimination when consider the breakdown according to white- vs. blue-collar status. Female workers get paid in relative terms slightly more than their relative productivity, which leads to the negative gaps reported in Table 3.5.A and 3.5.B. Yet, these are generally not statistically significant. It if only in large firms (100+) that we find evidence supportive of gender discrimination. Our system OLS estimate suggest a positive gap of about 6 percentage point, though the coefficient is not statistically significant (*i.e.* productivity higher than labour costs for women). System FGLS delivers a positive gap of 15 percentage points that is statistically significant, but only at the 1% level.

In interpreting the above empirical results it is helpful to bear in mind the benchmark definition of gender wage discrimination presented above: identifying market-wide and statistically significant gaps between gender productivity differentials and gender wage differentials. Recall that Hellerstein &Neumark (1995) empirical methodology does not provide a direct test of any particular theory of gender wage discrimination, rather, it supplies an empirical measure of the above benchmark concept of gender wage discrimination.

Nevertheless, although the Hellerstein and Neumark methodology does not provide a direct test for any particular theory of gender wage discrimination, we can still check which theories of gender wage discrimination are consistent with our empirical findings. Our core findings based on within-firm variation and the various extensions we carried out considering both firm- or worker traits *(i.e.* size and blue- or white-collar status) indicate that the null hypothesis of no gender wage discrimination holds. Indeed, although our results indicate that male and female labour do not provide the same services in the each firm, insofar as women, as a group, are significantly less productive than men, they do not reject the hypothesis that women get paid according to their lower productivity with respect to men.

Table 3.3: Separate estimation of Production Function and Labour Costs Equation

Method:	**1-OLS**	**2-Between**	**3-Intermediate inputs (Levinsohn-Petrin)**	**4-First-Differences**	**5-Within (firm fixed effects)**	**6-Within (firm fixed effects+ intermediate inputs LP)**
Productivity equation						
Share Women	-0.045***	0.014	-0.021*	-0.068*	-0.072**	-0.103***
p-value	0.0000	0.4897	0.0348	0.0163	0.0025	0,0002
Controls	capital. number of employees. hours worked per employee + fixed effects: year. nace1. region	capital. number of employees. hours worked per employee + fixed effects: year. nace1. region	capital. number of employees. hours worked per employee + fixed effects: firm	capital. number of employees. hours worked per employee + fixed effects: firm	capital. number of employees. hours worked per employee + fixed effects: firm	capital. number of employees. hours worked per employee + fixed effects: firm
Nobs.	59 980	59 980	49 582	49 395	59 980	49 575
Labour-cost equation						
Share Women	-0.171***	-0.117***	-0.131***	-0.013	-0.063***	-0.065***
p-value	0.0000	0.0000	0.0000	0.3814	0.0000	0.0000
Controls	hours worked per employee+ fixed effects: year. nace1. region	hours worked per employee+ fixed effects: year. nace1. region	hours worked per employee+ fixed effects: year. nace1. region	fixed effects: firm. year	fixed effects: firm. year	fixed effects: firm. year
Nobs.	60 713	60 713	49 581	50 110	60 713	49 581
Productivity vs labour cost differentials						
Productivity diff. (η)	0.95	1.02	0.98	0.90	0.91	0.87
Labour costs diff. (η^W)	0.83	0.88	0.87	0.99	0.94	0.94
Gap (η- η^W)	0.12	0.13	0.11	-0.09	-0.03	-0.06

*p < 0.05, **p < 0.01, *** p < 0.001

Table 3.4: Joint estimates of productivity and labour costs differentials. Within (firm fixed effects) + intermediate inputs (Levinsohn-Petrin). Cluster-robust estimation of standard-errors.

	Production diff. (η): ref=men	**Labour-cost diff (η^W): ref=men**	**Gap (η- η^W)**	**Wald Hyp. Test (η= η^W)**	
				χ^2	**Prob>χ^2**
System FGLS	0.936	0.941	-0.005	0.04	0.8473
System OLS	0.881	0.941	-0.060	1.14	0.2863

*p < 0.05, **p < 0.01, *** p < 0.001

a:Simultaneous estimation accounting for possible correlation between residuals

b:Equations are estimated separately

Table 3.5: Joint estimates of productivity and labour costs differentials. Breakdown by firm size and labour market status (p-values in italics). *Within (firm fixed effects)+ intermediate inputs (Levinsohn-Petrin). Cluster-robust estimation of standard-errors*

A System FGLS[a]

	Production diff. (η):	**Labour-cost diff (η^W)**	**Gap (η- η^W)**	**Wald Hyp. Test (η- η^W)**	
System FGLS*				**χ^2**	**Prob>χ^2**
Firm size	ref=men	ref=men			
1-49	0.86	0.91	-0.046	1.84	0.1744
50-99	0.96	0.93	0.029	0.26	0.6134
>=100	1.21	1.06	0.151*	5.47	0.0193
Gender/Status	ref=blue-collar men	ref=blue-collar men			
blue-collar women	0.84	0.88	-0.041	0.97	0.3246
white-collar women	1.20	1.23	-0.025	0.65	0.4186
white-collar men	1.35	1.41	-0.056*	4.33	0.0374

*p < 0.05, **p < 0.01, *** p < 0.001

B System OLS[b]

System OLS	Production diff. (η): ref=men	Labour-cost diff (η^W): ref=men	Gap (η- η^W)	Wald Hyp. Test (η= η^W) χ^2	Prob>χ^2
Firm size	ref=men	ref=men			
1-49	0.75	0.91	-0.154*	4.71	0.0300
50-99	0.86	0.93	-0.071	0.36	0.5459
>=100	1.12	1.06	0.059	0.21	0.6483
Gender/Status	ref=blue-collar men	ref=blue-collar men			
blue-collar women	0.80	0.83	-0.026	0.61	0.4356
white-collar women	0.96	1.16	-0.202	2.53	0.1120
white-collar men	1.09	1.32	-0.231	2.22	0.1366

*p < 0.05, **p < 0.01, *** p < 0.001

a:Simultaneous estimation accounting for possible correlation between residuals

b:Equations are estimated separately, but the estimates are used to construct a cluster-adjusted robust sandwich variance-covariance matrix.

3. Conclusion

In this chapter we used firm-level data from a matched employer-employee data set to test for the presence of gender wage discrimination in the Belgian labour market. We identified gender wage discrimination from within-firm variation and used Levinsohn and Petrin (2003) structural production function estimator to control for the endogeneity in input choice. Our findings indicate that, on average, women earn 6% less than men but also that they are collectively 6-12% less productive than men.

Our findings suggest that women are not systematically discriminated against in earnings in the Belgian labour market. In essence, these findings are consistent with the prediction of Becker (1957) that there are efficiency costs associated with gender-biased preferences by employers, and that competition should eliminate wage discrimination in the long run. The estimates of the gender labour costs differential we obtained also accord with those obtained in empirical studies using Oaxaca-Blinder decompositions based on wage equations to explain the sources of gender differences in pay in the Belgian labour market (Rycx & Tojerow, 2002). More importantly, due to the ability of Hellerstein & Neumark's methodology to supply a direct test for the gender wage discrimination hypothesis, we contribute with new evidence to the research programme dedicated to explaining the sources of the gender pay gap. Because we use firm-level data we are indeed able to estimate gender *productivity differences* alongside the traditional gender wage/labour costs differences, and show that the two are approximately aligned.

CHAPTER 4 – Assessing the (lack of) employability of senior women

1. Introduction

Employability is about having the capability to gain initial employment, maintain employment and obtain new employment in case job termination and/or unemployement. Most economists would agree that these labour market outcomes are, inter alia, driven by the ratio of individuals' productivity to their cost to employers. In other words, the willingness of employers to employ/recruit different categories of workers is influenced by their (relative) average labour cost per unit of output.

In this part of the Edipo project, we posit that one promising way of assessing the willingness of firms based in Belgium to employ at-risk groups is to focus simultaneously on firm-level productivity and pay (or labour costs), and analyse the sensitivity of the productivity-labour costs ratio to the workforce structure of firms. Here the focus is on the share of older women (see Box 1 for the mathematical exposition of the method).

Expanding the range of employment opportunities available to older workers will become increasingly important in most EU countries as demographics (ageing populations) and public policy will combine to increase the share of older individuals in the labour force. Across the EU, with the exception of some Nordic countries, there is also that older women are clearly less present in employment than older men. But this should change.

The first point we raise in this chapter is that a greying workforce will also become more female. Two elements combine in support of this prediction. The first one is the lagged effect of the rising overall female participation in the labour force (Peracchi & Welch, 1994). The second factor is labour policy. Policymakers will concentrate on promoting older women's employment because - conditional on a certain young- or prime-age participation record - women still leave the labour market earlier than men (Fitzenberger et al., 2004). The second focal point of this chapter is the idea that higher employment among the older segments of the EU population (male or female) will only materialise if firms are willing to employ these individuals. One cannot take for granted that older individuals who are willing to work - and are strongly enticed to do so because (early)retirement benefits are no longer accessible - do obtain employment. Anecdotal evidence abounds to suggest that firms "shed" older workers. Dorn & Sousa-Poza (2010) show, for instance, that involuntary early retirement is the rule rather than the exception in several continental European countries: in Germany, Portugal and Hungary more than half of all early retirements are, reportedly, not by choice. In short, there is a need to understand better the capacity of EU labour markets to adapt to ageing and feminizing workforces.

In this chapter we also use firm-level direct measures of productivity and labour cost. Our Belgian data permit a direct estimation of age-gender/productivity-labour cost ratio profiles, where the parameter estimates associated with the shares of older workers (male and female) in the workforce can be directly interpreted as conducive to weak or strong labour demand or employability (more on this in Section 2). Our measure of firms' productivity (valued added) enhances comparability of data across industries, which vary in their degree of vertical integration (Hellerstein et al., 1999). Moreover, we know with great accuracy how much firms spend on their employees. Some studies use individual information on gross wages, whereas we use firm-level information on annual gross wages plus social security contributions and other related costs. Our data also contain information on firms from the large and expanding services industry, where administrative and intellectual work is predominant, and where female employment is important. Many observers would probably posit that age and gender matters less for productivity in a service-based economy than in one where agriculture or industry dominates. Finally, it is worth stressing that our panel comprised a sizeable number of firms (9,000+) and covered a relatively long period running from 1998 to 2006.

We try to find evidence of a negative (or positive) effect on i) average productivity, ii) average labour costs and iii) the productivity-labour cost ratio of larger shares of older (male and female) workers (see Box 1, for the mathematical justification). We also employ the framework pioneered by HN, which consists of estimating production and/or labour cost functions that explicitly account for labour heterogeneity. Applied to firm-level data, this methodology presents two main advantages. First, it delivers productivity differences across age/gender groups that can immediately be compared to a measure of labour costs differences, thereby identifying the net contribution of an age/gender group to the productivity-labour cost ratio (which can be directly interpreted as conducive to weak or strong employability). Second, it measures and tests for the presence of market-wide impact on the productivity-labour cost ratio that can affect the overall labour demand for the category of workers considered.

Easy access to (early)retirement benefits and the financial disincentives to continue to work at older ages imbedded these regimes are the factors traditionally emphasized by economists to explain the country's low employment rate among individuals aged 50 and over. Here, we present evidence that the latter could also be demand-driven. Firms based in Belgium face financial disincentives to employing older workers - particularly older women. Our most important results in this respect are those derived from the regression of the productivity-labour cost ratio on the share of older men and women. Using prime-age men as a reference, we show that a 10%-points rise in the share of older men causes a moderate reduction in the productivity-labour cost ratio ranging from 0 to 0.88%. However, the situation is different for older women. Our preferred estimates suggest that a 10%-points expansion of their share in the firm's workforce causes a 1.8 to 2.1% reduction in the productivity-labour cost ratio; something that is likely to negatively affect their employability. Using prime-age women as a reference, we find that 10%-points expansion of old women's share causes a contraction of the productivity-labour cost ratio in the range of 1.04 to 2.14%. And these negative effects are even larger when we restrict the analysis to subsamples of firms (i.e. balanced panel, services industry). The ultimate point is that these results raise questions about the feasibility, in the current context, of a policy aimed at boosting the employment rate of older women.

The rest of the chapter is organized as follows. Section 2 is devoted to an exposition of the dataset. Section 3 contains the econometrics results. Our main conclusions are exposed in Section 4. That final section also contains a discussion of the various factors that may explain why older women (at least in Belgium) display a larger productivity and employability handicap than older men.

2. Data description

We have used a panel of around 9,000 firms with more than 20 employees, largely documented in terms of sector, location, size, capital used, labour cost levels and productivity (value added). These observations come from the Bel-first database. Via the so-called Carrefour data warehouse, using firm identifiers, we have been able to inject information on the age/gender of (all) workers employed by these firms, and this for a period running from 1998 to 2006.

Descriptive statistics are reported in Tables 4.1-4. Tables 4.2 and 4.3 suggest that firms based in Belgium have been largely affected by ageing over the period considered. Table 4.2 shows that between 1998 and 2006, the mean age of workers active in private firms located in Belgium rose by almost 3 years: from 36.2 to 39.1. This is very similar what has occurred Europe-wide. For instance Göbel & Zwick (2009) show that between 1997 and 2007 the average age of the workforce in the EU25 has risen from 36.2 to 38.9.

Table 4.3 also shows that, in the Belgian private economy, between 1998 and 2006, the percentage of old male workers (50-65) has risen steadily from 10% to almost 15%. And the proportion of older women has risen even more dramatically, from 2% to 4.1%. While starting from a low level in 1998 (2.13%), the rise of the share of older women has been of more than 96% in cumulative terms. The corresponding figure for older men is only 48 %.

What may explain this gender asymmetry? We would formulate two (non-mutually exclusive) explanations. The first one, already mentioned above, is the "lagged effect" of surge of female participation in the labour market, itself explained by the lowering of the birth rate and a surge in the number of women accessing tertiary education. The second hypothesis is that of the impact of the pension reform that took place in Belgium in 1997. Before 1997, the legal age of retirement was 60 for women, but 65 for men. The European court of Justice considered this as a form of gender discrimination.

The exact timing of gender alignment decided in 1997 is exposed in Table 4.4. The point is the coincidence between the calendar of the 1997 reform (first step towards alignment in 1997, full alignment in 2007) and that of our panel (1998-2006). Of course, there is no certainty that the increase in the share of older women in our data is primarily due to the reform. But one cannot exclude this hypothesis. What is more, it has some methodological interest as to the econometric identification of the consequences of ageing workforces.

If we assume that at least part of the increase in the share of elderly women can be ascribed to the 1997 reform, then we could argue that we are dealing with a “natural experiment”. And the latter could help assess the impact of ageing on firm-level productivity. We will argue hereafter that there is a chance that our estimates for older female workers are intrinsically less biased due to selectivity than those obtained for older men. We will elaborate on this in the final section of the chapter.

Table 4.1: Bel-first-Carrefour panel. Main variables. Descriptive statistic.

Variable	Mean	Std. Dev.
Productivity (ie.value added) per worker (th. €) (log)	4.076	0.565
Labour cost per worker (th. €) (log)	3.706	0.381
Productivity-Labour cost ratio/markup	0.372	0.404
Capital (th. €) (th. €) (log)	6.835	1.752
Number of workers (th. €) (log)	3.937	0.994
Share of 18-29 (Male)	0.287	0.163
Share of 30-49 (Male)	0.309	0.152
Share of 50-65 (Male)	0.122	0.103
Share of 18-29 (Female)	0.137	0.153
Share of 30-49 (Female)	0.115	0.117
Share of 50-65 (Female)	0.031	0.050
Use of intermediate inputs (th. €) (log)	8.939	1.575
Share of blue collar workers in total workforce	0.544	0.351
Share of Manager in total workforce	0.010	0.042
Number of hours worked annually per employee (log)	7.377	0.163
Number of spells	8.730	0.944

Source: Bel-first-Carrefour

Table 4.2: Bel-first-Carrefour panel. Basic descriptive statistics.
Evolution of shares of workers between 1998 and 2006

Year	Mean age (year)	Share of 18-29 (%)	Share of 30-49 (%)	Share of 50-65 (%)
1998	36.15	48.58%	39.35%	12.08%
1999	36.43	46.98%	40.37%	12.67%
2000	36.64	45.84%	40.90%	13.26%
2001	37.00	44.24%	41.77%	14.00%
2002	37.37	42.61%	42.76%	14.64%
2003	37.96	40.64%	43.12%	16.24%
2004	38.33	39.17%	43.77%	17.06%
2005	38.72	37.66%	44.43%	17.91%
2006	39.10	36.33%	44.66%	19.00%

Source: Bel-first-Carrefour

Table 4.3. Shares of male vs female old workers (50-64).
Private sector economy. Belgium. 1998-2006

	Share of old men	**Share of old women**	**Evolution share of old men (1998=100)**	**Evolution share of old women (1998=100)**
1998	9.92%	2.13%	100.00	100.00
1999	10.33%	2.30%	104.08	107.62
2000	10.73%	2.48%	108.13	116.25
2001	11.22%	2.72%	113.06	127.53
2002	11.69%	2.92%	117.76	136.82
2003	12.90%	3.31%	130.02	155.06
2004	13.47%	3.56%	135.75	166.73
2005	14.04%	3.83%	141.43	179.29
2006	14.72%	4.20%	148.31	196.86

Source : Bel-first, Carrefour

Table 4.4. Pension reform of 1997.
Calendar of the alignment of legal age of retirement for women on that of men.

	1996	**1997**	**2000**	**2003**	**2006**	**2009**
Male	65	65	65	65	65	65
Female	60	61	62	63	64	65

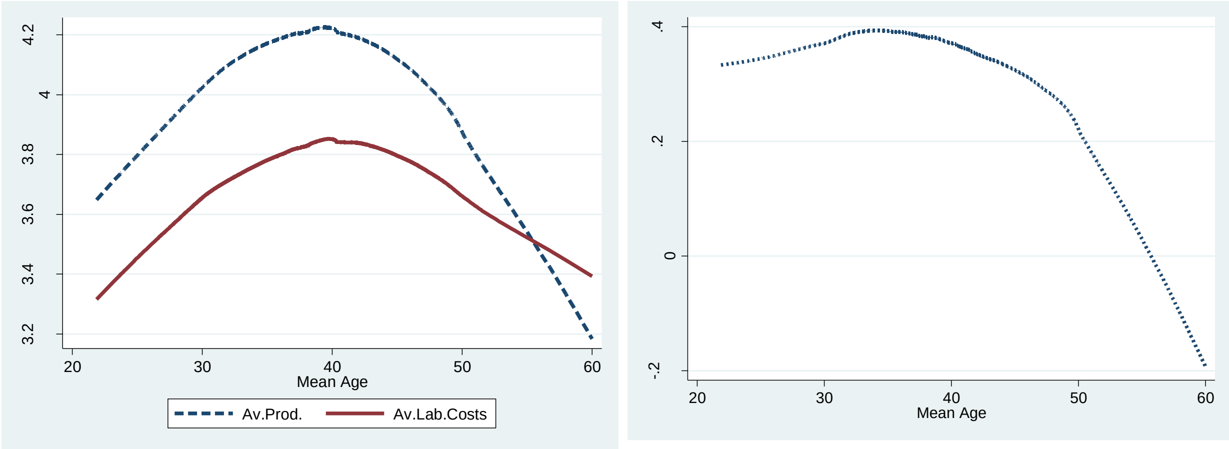
Source : www.socialsecurity.be

Intermediate inputs pay a key role in our analysis, as they are central to one of the two strategies we use to overcome the simultaneity/endogeneity bias (see Box 2). The level of intermediate inputs used by a firm is calculated here as the difference between its turnover (in nominal terms) and gross value-added. It reflects the value of goods and services consumed or used up as inputs in production by that firm, including raw materials, services and various other operating expenses.

Figure b.1 (left panel) displays how the (log of) average productivity and the (log of) average labour costs evolve with mean age, for the year 2006 subsample. The right panel of Figure b.1 corresponds to the difference between these two curves, which is equal to the productivity-labour cost ratio. These stylised facts suggests that, in the Belgian private economy, the productivity-labour cost ratio rises up to the (mean) age of 35-38 where it reaches 40%, but then declines steadily. It falls below 10% when mean age exceeds 55.

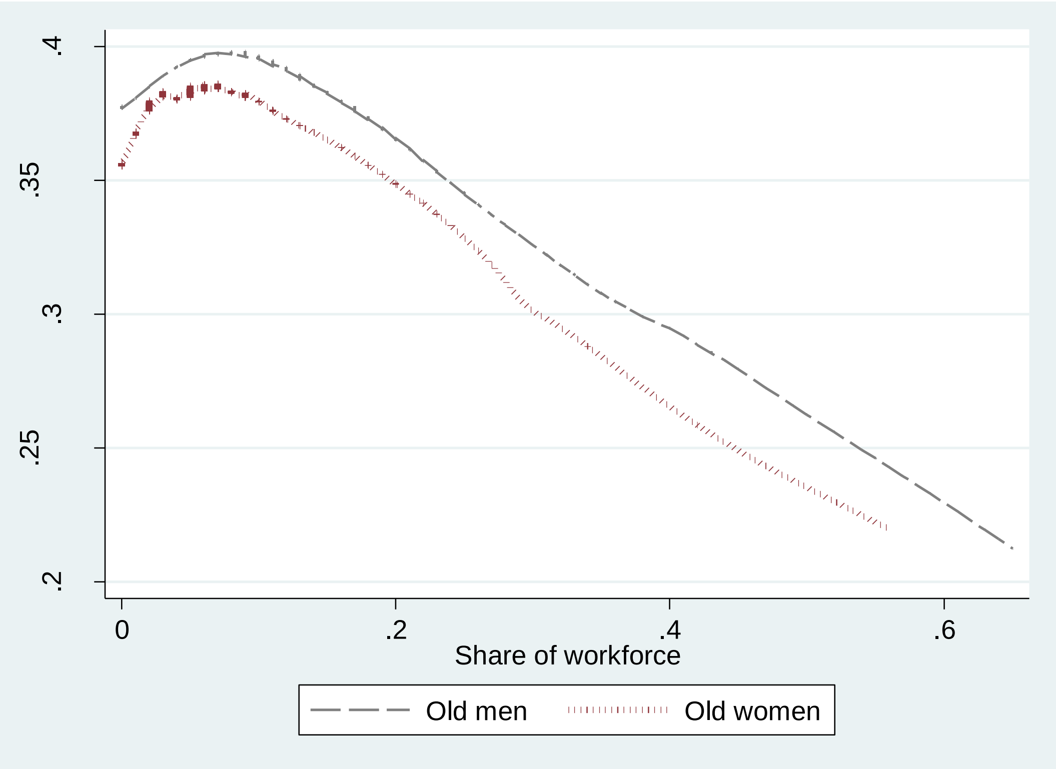
Figure 4.2 is probably more directly echoing the main issue which is raised in this chapter. It depicts the relationship between the share or older (50-64) men or women and the productivity-labour cost ratio. It suggests that firms employing shares of older men and women in excess of the 7-8% threshold have a significantly smaller productivity-labour cost ratio. It is also shows that firms employing a given share of older women systematically achieve a lower ratio than firms employing the same share of older men.

Figure 4.1: (Left panel) Average productivity and average labour costs. (Right panel) Productivity-Labour cost ratio (%) according to mean age. Year 2006



Curves on display correspond to locally weighted regression of *y* (i.e. log of average productivity, log of average labour cost [left panel] and labour costs ratio [right panel]) on *x* (i.e. mean age). OLS estimates of *y* are fitted for each subsets of *x*. This method does not required to specify a global function of any form to fit a model to the data, only to fit segments of the data. It is thus semi-parametric.

Figure 4.2: Productivity-Labour cost ratio (in %) according to share of older men or women



Curves on display correspond to locally weighted regression of *y (productivity-labour cost ratio)* on *x (shares).* It does this by fitting an OLS estimate of *y* for each subsets of *x*. This method does not required to specify a global function of any form to fit a model to the data, only to fit segments of the data. It is thus semi-parametric.

A weakness of our dataset is that it does not contain the workers' educational attainment. The point is that younger cohorts are better-educated and, for that reason, potentially more productive than older ones. As we do not control for educational attainment, how large is the risk that our estimates confound age and cohort/education, and consequently exaggerate the age-related productivity handicap?

Not so much, we think, for three reasons. First, although we do not observe education, our vector of controls comprises good firm-level proxies for education (i.e. the share or blue-collar workers and the share of managers). Second, in this chapter the identification of the effect of age on productivity is driven by younger (and presumably better-educated) cohorts entering the 50-64 age-bracket. With FD, identification comes from the confrontation of production changes recorded between t and t-1 and the simultaneous change (presumably rise) of the share of older workers. But in a panel, cohort/year-of-birth and time of observation are monotonically related: individuals belonging to the 50-64 age-band in t are likely to belong to younger (and better-educated) cohorts than those observed in t-1 in the same age band. In short, with FD identification of the consequence of ageing workforces is driven by better-educated individuals. Sceptics will rightly argue that with FD identification rather comes from the comparison between i) productivity gains achieved by firms with rising shares of old (50-64) workers ii) and those obtained by firms with no (or less of) such rises. How do the two types of firms compare in terms of cohort (and thus educational) changes between t and t-1? The workers' average year of birth has probably risen more in the second type of firms, due to a more pronounced propensity to replace older workers by younger (better-educated) ones. This leads us to our third argument. Unobserved asymmetries across firms in terms of cohort (and education) dynamics are unlikely to bias results obtained in an HN framework. This is because, with HN, productivity is measured in relative terms. The estimated coefficient for the share of 50-64 workers corresponds to the relative productivity of that group vis-à-vis the reference group (i.e. prime-age workers). If, within each firm, the pace at which younger/better-educated cohorts enter the prime-age and the old age brackets does not vary significantly, firm-specific cohort biases will just cancel out.

3. Econometric results

Table 4.6 presents the parameter estimates of the average productivity, labour costs and productivity-labour cost ratio equations (see Box 1), under four alternative econometric specifications. Note that, the third equation being the difference between the two previous it is logical to verify that $\eta-\eta W\approx\eta R$.for each age/gender category. Standard errors on display have been computed in a way that accounts for firm-level clustering of observations. To get the results on display in Table 4.5 we use all available observations forming of our (unbalanced) panel.

The first set of parameter estimates comes from OLS, using total variation [1]. Then comes first differences (FD), where parameters are estimated using only within-firm variation [2]. Model [3] combines FD and the IV-GMM approach using internal lagged labour inputs as instruments (FD-IV-GMM). The last model [4] combines FD and the ACF intermediate-goods proxy idea (FD-ACF).

Estimations [3] [4] in Table 4.6 are a priori the best insofar as i) the parameters of interest are identified from within-firm variation to control for firm unobserved heterogeneity, and ii) that they control for short-term endogeneity biases either via the use of ACF's intermediate input proxy, or internal instruments.

OLS results suffer from unobserved heterogeneity bias. Even the inclusion of controls in Fit, mostly a large set of dummies, is probably insufficient to account for firm-level singularities that may affect simultaneously firms' productivity and age structure. First-differencing as done in [2] is still the most powerful way out of this problem. Heterogeneity bias might be present since our sample covers all sectors of the Belgian private economy and the list of controls included in our models is limited. Even if the introduction of the set of dummies (namely year, sector) in Fit can account for part of this heterogeneity bias, first-differencing as done in [2], [3] or [4] is still the most powerful way out. But first differences alone [2] are not sufficient. The endogeneity in labour input choices is well documented problem in the production function estimation literature (e.g. Griliches & Mairesse, 1995) and also deserved to be properly and simultaneously treated. And this is precisely what we have attempted to do in [3] and [4] by combining first differences with techniques like IV-GMM or ACF.

To assess the credibility of our FD-IV-GMM approach [3] we performed a range of diagnostic tests. First, an Anderson correlation relevance test. If the correlation between the instrumental variables and the endogenous variable is poor (i.e. if we have "weak" instruments) our parameter estimate may be biased. The null hypothesis is that the instruments are weak (correlation in nil). Rejection of the null hypothesis (low p-values) implies that the instruments pass the weak instruments test, i.e. they are highly correlated with the endogenous variables. In all our FD-IV-GMM estimates reported in Table 6 our instruments pass the Anderson correlation relevance test. Second, to further assess the validity of our instrument we use the Hansen-Sargan test. – also called Hansen's J test – of overidentifying restrictions. The null hypothesis is that the instruments are valid instruments (i.e., uncorrelated with the error term), and that the instruments are correctly "excluded" from the estimated equation. Under the null, the test statistic is distributed as chi-square in the number of overidentifying restrictions. A failure to reject the null hypothesis (high p-values) implies that the instruments are exogenous. In all our FD-IV-GMM estimates we cannot reject the null hypothesis that these restrictions are valid. In Table 4.6, parameter estimates (η) for the average productivity equation support the evidence that older worker (50-65) - both men and women - are less productive than prime-age (30-49) male workers (our reference category). Sizeable (and statistically significant) negative coefficients are found across the range of models estimated. Those from the FD-ACF model [4] suggest that an increase of 10%-points in the share of old male workers depresses productivity by 1.54%-points. Model [3], based on FD-IV-GMM, points at a smaller (not statistically significant) drop by only 0.37%t.

As to old women both FD-IV-GMM [3] and the FD-ACF model [4] deliver large negative estimates of the impact of larger shares of old women on productivity. An increase of 10%-points in the share of older female workers reduces productivity by 2.32% [3] to 3.81% [4]. Turning to the average labour cost coefficients (ηW), we find some evidence of lower labour cost for older men and women. Estimates for model [3] show that a 10%-points rise of the share of older male (female) workers reduces average labour cost by 0.31%-point (0.49%-point respectively). Evidence from model [4] is supportive of wage declines of 0.67% for men, and 2.96 %-points for women. The slightly lower labour costs for older women could reflect the fact that they have accumulated lower tenure in firms; something that, ceteris paribus, may reduce their cost to employ in a country where seniority plays an important role in wage formation (BNB, 2010).

However, regarding the labour demand for older men and women, the most important parameters are those of the productivity-labour cost ratio equation (ηR). Their sign informs as to whether a lower productivity is fully compensated by lower labour costs. Remember that we posit that a negative (and statistically significant) coefficient is a indication that the category of workers is less employable than the reference category. Results for old men are mixed. Model [3] delivers a coefficient that is not statistically different from O. Model [4] suggests that a 10%-points rise of their share causes a modest 0.88% reduction of the productivity-labour cost ratio. The situation is quite different for old women. Model [3] suggests that a 10%-points expansion of their share in the total workforce causes a 1.8% reduction of the productivity-labour cost ratio. And model [4] points to a 2.11% drop of that ratio.

Table 4.6 contains a series of important results that can be derived from a further analysis of those displayed in Table 4.5. The first column simply reproduces the estimates for the average productivity and productivity-labour cost ratio equations, using our preferred estimation strategies [3] [4]. The following columns contain the results of three hypothesis tests aimed at answering key questions about age and gender. First, are old women (50-64) less productive [and less employable, due to a lower productivity-labour cost ratio] than old men? The question amounts to verifying that $\eta 3m>.\eta 3f$ [$\eta R3m>\eta R3f$] in absolute value and testing H0: $\eta 3m=\eta 3f$ for productivity [H0: $\eta R3m=\eta R3f$ for employability]. Results for FD-IV-GMM model [3] point to a 1.95% productivity handicap for old women relative to old men, and an employability handicap of 1.78%. Both estimates are highly statistically significant. They mean that a 10% rise of the share of older women is causing an additional 1.95% [1.78%] reduction of labour productivity [productivity-labour cost ratio], compared with a similar increase of the share of older men. Controls in Table 4.6 are the following: capital, number of employees, hours worked per employee, share of blue-collar workers, share of managers + firm fixed effects.

The second question that can be addressed is whether old women's productivity[employability] handicap relative to old men is driven by more pronounced effects of age on women than on men's productivity[employability].

We can first examine, for each gender separately, how age affects productivity[employability] using the prime-age category as a reference .As already stated above, the evidence for old vis-à-vis prime-age male workers (ie. estimated $\eta 3m$ [$\eta R3m$]) is mixed. Results for the FD-IV-GMM model [3] suggest an absence of significant deterioration of productivity[employability], whereas FD-ACF model [4] is supportive of a small deterioration. A 10%-points rise of the share of old men causes a 1.54% [0.88] decline of productivity[employability]. Assessing the situation of older women relative to prime-age women is less immediate and requires hypothesis testing (ie. rejecting H0: $\eta 2f =\eta 3f$ [H0: $\eta R2f =\eta R3f$]). Results for FD-IV-GMM model [3] points to a 1.1% productivity handicap (not statistically significant at the level of 5 percent) for old women relative to prime-age women. In terms of employability, the handicap is of 1.04% (also not statistically significant). Results with FD-ACF model [4] are larger in magnitude and statistically significant, namely a productivity handicap of 3.31%-, and an employability handicap of 2.14%.

Table 4.5. Parameter estimates (*standard errors*[£]). Older (50-64) male/female and prime-age (30-49) female workers productivity (η), average labour costs(η^{w}) and productivity-labour cost ratio (η^{R}). Overall, unbalanced panel sample.

	[1]-OLS	**[2]-First Differences (FD)**	**[3]- FD-IV-GMM**	**[4]- FD + intermediate inputs ACF[$]**
Share of 50-64 (Men)				
Productivity (η_{3m})	-0.218***	-0.071**	-0.037	-0.154***
std error	*(0.024)*	*(0.028)*	*(0.027)*	*(0.034)*
Labour Costs (η^{w}_{3m})	-0.170***	-0.017	-0.031**	-0.067***
std error	*(0.013)*	*(0.012)*	*(0.015)*	*(0.021)*
Prod.-Lab. Costs ratio (η^{R}_{3m})	-0.054***	-0.054**	-0.002	-0.088***
std error	*(0.020)*	*(0.027)*	*(0.037)*	*(0.024)*
Share of 30-49 (Women)				
Productivity (η_{2f})	-0.281***	-0.031	-0.119***	-0.050
std error	*(0.021)*	*(0.032)*	*(0.045)*	*(0.055)*
Labour Costs (η^{w}_{2f})	-0.347***	-0.043***	-0.037**	-0.081**
std error	*(0.012)*	*(0.014)*	*(0.019)*	*(0.031)*
Prod.-Lab. Costs ratio (η^{R}_{2f})	0.019	0.012	-0.076*	0.003
std error	*(0.017)*	*(0.031)*	*(0.044)*	*(0.044)*
Share of 50-64 (Women)				
Productivity (η_{3f})	-0.638***	-0.210***	-0.232***	-0.381***
std error	*(0.038)*	*(0.053)*	*(0.070)*	*(0.080)*
Labour Costs (η^{w}_{3f})	-0.665***	-0.056**	-0.049*	-0.296***
std error	*(0.021)*	*(0.023)*	*(0.029)*	*(0.049)*
Prod.-Lab. Costs ratio (η^{R}_{3f})	-0.017	-0.153***	-0.180***	-0.211**
std error	*(0.031)*	*(0.051)*	*(0.068)*	*(0.070)*
#Obs.	77,847	67,678	50,176	38,296
Controls	All data are deviations from region+ year interacted with NACE2 industry means. See appendix for NACE2 classification of industries			
	capital, number of employees, hours worked per employee[a], share of blue-collar workers, share of managers	capital, number of employees, hours worked per employee[a], share of blue-collar workers, share of managers + fixed effects: **firm**	capital, number of employees, hours worked per employee[a], share of blue-collar workers, share of managers + fixed effects: **firm**	capital, number of employees, hours worked per employee[a], share of blue-collar workers, share of managers + fixed effects: **firm**
Orthogonality conditions/instruments used to identify endog. labour shares			Second differences and lagged second differences	Innovation in $\omega_{it⫫}$ *lag1-3* labour shares Innovation in ωit⫫ lag1-3 labour shares
Identification tests			**IV relevance**: Anderson canon. corr. LR statistic√ **Overidentifying restriction**: Hansen J statistic √	

a: Average number of hours worked by employee on an annual basis, which is strongly correlated to the incidence of part-time work.

Table 4.6 – Parameter estimates (*standard errors*[£]) and hypothesis testing. Older (50-64) male/female and prime-age (30-49) female workers productivity (η), average labour costs(η^{W}) and productivity-labour cost ratio (η^{R}). Overall, unbalanced panel sample.

	Coefficient	Hyp Test $\eta_{3f}=\eta_{3m}$ (old			Hyp Test $\eta_{3f}=\eta_{2f}$ (old women			Hyp Test $\eta_{3f}-\eta_{2f}=\eta_{3m}$ (within gender		
		$\eta_{3f}-\eta_{3m}$	F	Prob >F	$\eta_{3f}-\eta_{2f}$	F	Prob >F	$(\eta_{3f}-\eta_{2f})-\eta_{3m}$	F	Prob >F
[3] - FD- IV-GMM										
Men 50-64 (η_{3m})	-0.037 *(0.027)*									
Women 30-49 (η_{2f})	-0.119*** *(0.045)*	-0.195**	6.67	0.0098	-0.112	2.57	0.1089	-0.075	0.89	0.3452
Women 50-64 (η_{3f})	-0.232*** *(0.070)*									
Prod.-Lab. Costs ratio										
Men 50-64 (η^{R}_{3m})	-0.002 *(0.037)*									
Women 30-49 (η^{R}_{2f})	-0.076** *(0.044)*	-0.178*	5.91	0.015	-0.104	2.35	0.1257	-0.102	1.72	0.1891
Women 50-64 (η^{R}_{3f})	-0.180*** *(0.068)*									
#obs	50,176									
[4]- FD + ACF intermediate										
Men 50-64 (η_{3m})	-0.154*** *(0.034)*									
Women 30-49 (η_{2f})	-0.050 *(0.055)*	-0.227**	6.88	0.0087	-0.331***	11.61	0.0007	-0.177	2.67	0.1022
Women 50-64 (η_{3f})	-0.381*** *(0.080)*									
Prod.-Lab. Costs ratio										
Men 50-64 (η^{G}_{3m})	-0.088*** *(0.024)*									
Women 30-49 (η^{G}_{2f})	0.003 *(0.044)*	-0.123	2.55	0.1106	-0.214*	5.52	0.019	-0.126	1.60	0.2056
Women 50-64 (η^{G}_{3f})	-0.211** *(0.070)*									
#obs	38,296									

Furthermore, we can test whether age affects more women's than men's productivity[employability] by testing H0: $\eta R3f - \eta R2f = \eta R3m$ [H0: $\eta 3f - \eta 2f = \eta 3m$]. Results point to a 0.7% to 1.77% productivity handicap of women vis-à-vis men in terms of age-related productivity decline, and a 1.02% to 1.26% handicap in terms of employability decline. But none of these estimates are statistically significant at the level of 5 percent.

4. Conclusion

As a socio-economic phenomenon, population ageing in Europe will affect more than its welfare systems, as it will also affect the age structure of the workforce. In particular, the share of older workers (aged 50+) will rise significantly due to demographics. And this trend will be reinforced by policies aimed at maintaining more of those older individuals in employment. Another point we highlight in this chapter is that a greying European workforce should also become more female. There is indeed robust evidence that older women are still under-represented in employment in comparison with older men. But this should change due to the combined effect of two elements. First, participation rates in the 50-60 age range will partially align with those currently observed in some Nordic countries

(Sweden, Iceland), because successive cohorts of women with an increasing history of youth and prime-age participation are reaching older ages. Second, labour policy will try to close the gender participation gap that persists beyond 50, independently of the above-mentioned trend.

Optimists may believe that an ageing and feminized workforce will have only a minimal impact on firms' performance and on labour markets. This chapter contains evidence, based on the analysis of private-economy firm-level panel data, suggesting the opposite. We show that the age/gender structure of firms located in Belgium is a key determinant of their productivity-labour cost ratio. Employing a larger share of female workers aged 50-64 could translate ceteris paribus a lower markup between productivity (ie value added) and labour cost.

Our results show that, using prime-age men as a reference, an increase of 10%-points in the share of older female workers (50-64) depresses firms' productivity-labour cost ratio by 1.8 to 2.1%, depending on the estimation method and the sample chosen. The equivalent results for old men a moderate reduction in the productivity-labour cost ratio ranging from 0 to 0.88%. A closer look at the results reveals three important things.

First, the handicap of old female workers vis-à-vis old male workers is driven by a lower productivity that is not compensated for by lower average labour costs.

Second, older women are collectively less productive and employable than prime-age women.

Third, some of our results — obtained when focussing on balanced panel data and the service industry data — also support the idea that age affects women's productivity[employability] more than men's. In short, older women's employability handicap vis-à-vis older men stems from a productivity handicap caused by a more pronounced effect of age, which is not compensated by lower labour costs.

There is no doubt that welfare institutions played a role in lowering the country' supply of old labour, and have contributed to its low employment rate, singularly amongst women. According to Eurostat, in the first quarter of 2010, only 36% of individuals aged 55-64 were employed; which is 11.1%-points lower than the European average (EU 15). What is more, old women's employment rate (barely 30%) lags behind that of men (44%). In Belgium, qualifying for early retirement benefits is indeed relatively easy by international standards. While the age of 58 is a priori the minimum access age, a lower age of 55, 56 or 57 is possible in some sectors (steel, glass, textile, etc.). Even more pronounced reductions in the minimum age are possible when the company is recognized as being in financial trouble, under which circumstance the age can be brought down to 52 years, or even 50.

These social welfare determinants of the supply of old labour have traditionally been emphasized by economists to explain the country's particularly low employment rate among individuals aged 50 and over. Our main point is that this chapter contains evidence that the latter could also be demand-driven. Firms based in Belgium face financial disincentives to employing older workers - particularly older women.

We would like to also briefly mention some elements that should be held in mind when interpreting our results. First, only "average firm profiles" are calculated, which may imply that we overlook the capacity of some firms to neutralize the effect of age and gender on productivity, by implementing ad hoc measures that compensate for the age/gender-related loss of performance.

Second. This chapter is focused on the ratio between labour productivity and labour costs which is, without doubt, an important metric for employers. However, many observers would rightly argue that ultimately employers will care about financial survival and profits. Can it be the case that firms can employ older workers, singularly older women, and still make a profit or simply survive? First of all, remember that what is at stake here is not the financial survival of firms. All that we show in this chapter is that firms employing older women (and to a lesser extent older men) have to live with a lower (but still positive) markup between i) what they manage to produce per worker and ii) how much they spend to remunerate them. Beyond, how does this ultimately translate in terms of profits (i.e. return on capital)? The answer depends on the amount of capital in use per capita in firms with larger shares of older female workers. If it is the same as in other firms employing a younger or more masculine workforce, then returns will be lower, and this will further entice firms to reduce their demand of older female workers. Alternatively, these firms could operate with a lower capital base, in order to maintain returns. That could somehow preserve labour demand, but implies than an older and more feminized workforce will lead to the expansion of activities than are intrinsically less capital-intensive. This raises important issues (e.g. the degree of complementarity between young/old labour and capital) that go beyond the scope of this chapter, but certainly call for more research by economists with an interest in ageing.

Third. The worker sample that used here might not be representative of the entire population of older individuals aged 50-64. This means that there is a risk of a selection bias, in particular due to early ejection from the workforce of less productive/motivated older (male or female) workers. To the extent that this selection bias is an issue, we could view our estimated coefficients for older workers' productivity as lower boundaries (in absolute value). In other words, we potentially underestimate the productivity (and possibly also the employability) handicap of older workers.

To conclude, we would like to elaborate on some of the reasons that could explain the old female (relative) handicap highlighted in this chapter, particularly the factors driving their apparent productivity handicap.

Selectivity bias could be less pronounced for older women. Our data show that in Belgium, between 1996 and 2006, there has been a more pronounced rise of employment among older women than older men. If only a fraction of that extra rise can be ascribed to the 1997 reform, then part of their productivity handicap, as identified it in this chapter, could be the consequence of a exogeneous "natural experiment". Consequently, the tendency of our coefficients to underestimate the productivity handicap of older individuals could be less pronounced for older women than older men. Simply said, our estimates of the firm-level performance of older female workers could better reflect the actual productivity performance of older individuals than the estimates we get from the observation of older male workers.

Gender health gap could also be an issue (van Oyen et al., 2010; Case & Paxson, 2004). Women in Belgium — as in the US and many other advanced economies — have worse self-rated health, visit GPs more often, and have more hospitalization episodes than men, from early adolescence to late middle age. This said, the existing evidence suggests that this health gender gap tends to shrink when individuals turn 50 and more.

Lastly, in Belgium, like throughout much of the OECD, more and more people aged 50-64 need to provide informal care to their old parents aged 70+ while, perhaps, they are still intensively supporting their children who, for example, need baby-sit help. The point is that informal carers are predominantly female aged 50-64 (OECD, 2011). Caring responsibilities may cause burnout and stress, and lead to a lower attachment to the labour force, that is not properly captured by our data. All this could ultimately translate in to lower firm-level productivity.

CHAPTER 5 – Wages and productivity of male and female part-time work

1. Introduction

Over the past three decades, part-time jobs have become a prominent feature of many structural labour market changes in Europe and North America, and different scholars have identified part-time employment as one of the main factors underpinning processes of job flexibilization (Branine 1999; Edwards and Robinson 2000). Given that this type of employment majoritarily concerns women, it also raises issues linked to gender equality and the way in which contemporary societies organize the reconciliation of job market participation with non-market activities (Connolly and Gregory 2010).

In this chapter we provide quantitative results for the relationship between the firm's composition of labour in terms of working hours and gender, on the one hand, and the firm's average hourly wage and average productivity on the other hand. The paper contributes to the literature on part-time work by estimating the effect of male and female part-time employment on productivity, wages, and productivity-wage gaps for the case of Belgian private-sector firms; we are notably able to measure potential economic rents.

2. Review of the literature

In this section we present three partly overlapping explanations for differences in hourly pay and productivity between part- and full-time workers and discuss their potential gender dimension.

Cost structure of employment

A first cluster of theories concerns the cost structure of firms. The existence of fixed costs – including administrative costs of maintaining records for each employee, recruitment and firing costs, and fringe benefits that are independent of working hours – generally implies that total labour costs do not increase proportionally with working hours (Montgomery 1988). As a result, part-time workers are relatively more costly and may therefore receive lower wages. It can also be argued that part-time workers may give rise to coordination costs (Lewis 2003): while part-time jobs can be easily managed in a Taylorist organisation in which workers can be substituted for each other, organisations that rely on task-specific skills may experience that part-time jobs create communication gaps or jeopardize output continuity (Bonamy and May 1997). The cost advantages and disadvantages associated with managing a part-time workforce have been recorded in a qualitative analysis of the nursing profession in the UK by Edwards and Robinson (2004). Questionnaire respondents identified disadvantages such as communication problems, an increase in administrative costs, overhead expenditures associated with training and difficulties regarding service continuity.

Female employment might also affect the cost structure if employers associate female jobs with relatively higher costs, for instance due to faster turn-over or more absenteeism due to the fact that women are more likely to be constrained by domestic or care duties and have more fractured career patterns due to maternity leaves.

Fixed labour costs and coordination costs could decrease the relative remuneration of part-time workers to the extent that employers pass on these costs by reducing part-time wages. Given that the majority of part-time workers are women, additional costs associated with female employment could also be passed on to employees and acerbate the resulting difference in part-time and full-time remuneration.

Labour productivity

The second cluster of theories is concerned with differences in labour productivity. Most theories concern productivity gaps between full- and part-time jobs; it is rare to find arguments that associate productivity differences directly with gender. A well-known argument against part-time work is that daily start-up costs imply that productivity picks up only slowly during the working day. As a result, the worker's productivity during the last hour of work exceeds average productivity (Barzel 1973). However, other authors point to the tiredness associated with long working hours and argue that part-time workers could outperform their fatigued full-time colleagues (Brewster and al. 1994). In addition, part-time jobs might allow individuals to make better use of the circadian rhythm and reduce the amount of stress, potentially leading to higher performance (Pierce and Newstrom 1983; Baltes et al. 1999).

A challenge associated with part-time work is that managers might not always adjust expectations correctly when employees move from full to part-time positions, thus influencing the effectiveness of flexible work policies (Stanworth 1999). For instance, working reduced hours often entails to deal in a shorter time with what effectively remains a full-time workload (Edwards and Robinson 2000; Lewis 2001, 2003), a phenomena that could lead to a gap between productivity and wages of part-time workers.

Productivity gains from part-time work can be realised by dividing work hours over a larger pool of employees; by extending opening hours without increasing payroll costs; or by exploiting firm-specific capital more intensively. In short, part-time arrangements often mean that employers can react more flexibly to market changes and needs. Shepard et al. (1996) indeed argued that flexible working hours and alternatives to the traditional full-time work schedule might increase productivity and wages; for instance, part-time wage premia have been observed in sectors facing seasonal or fluctuating demand that cannot be managed through the carrying of inventories. In this context, employers may pay higher wages to part-time workers in order to staff highly productive peak periods. Results in Hagemann et al. (1994), using a survey of 3,000 employees in five German companies from different industries showed that: i) standard part-time jobs (i.e. employees working fewer hours per day) increases motivation and reduces absenteeism; ii) cyclical part-time jobs enable to manage peaks and troughs in demand more efficiently (e.g. in industries such as tourism and banking); and iii) shift-based part-time jobs might extend operating hours, leading to a more intense use of capital. Productivity-enhancing effects of part-time work have also been found in a study using the National Organizations Survey of US firms by Perry-Smith and Blum

(2000) and in estimates based on the employer–employee cross-sectional dataset of Dutch pharmacies by Künn-Nelen et al. (2013).

Policies in favour of part-time work are often justified by the idea that reduced hours enable individuals with multiple roles (especially women) to reconcile commodified and private work, thereby leading to higher productivity. While the direct effect of part-time arrangements on productivity is rarely measured, there is some evidence that part-time jobs reduces stress (a phenomenon arguably related to multiple duties at work and home). For instance, the study of Branine (2003) based on data obtained from a questionnaire and interviews of hospital staff in the UK, France, and Denmark found that part-time work is usually associated with low absenteeism and less stress. Moreover, the study by Edwards and Robinson (2000) used qualitative analysis of the metropolitan police service in the UK to document that part-time work helps to retain experienced staff who would otherwise exit the labour force (especially women) and to increase job satisfaction and commitment.

Finally, an important productivity effect of part-time employment relates to human capital. Indeed, many authors hypothesize a negative relationship between working hours and involvement in training (Jepsen, 2001). One of the underlying mechanisms is that part-timers might arguably be less committed to career goals and that domestic responsibilities and career interruptions could crowd out personal investments in training, but employers might also be less willing to invest in the training of part-time workers. Empirical research tends to back the claim of lower human capital accumulation among part-timers. Felstead et al. (2000) have shown that workers moving from full- to part-time employment are likely to experience a stagnation of skills. Walby and Olsen (2003) found that women working in part-time jobs are the least likely to improve their skills. Branine (2003) also presented evidence that part-time work is associated with low employment commitment and relatively lower skills. Edwards and Robinson (2000) cited the marginalization of part-time workers in terms of training among the disadvantages of these work arrangements. On average, the part-time nurses interviewed by Edwards and Robinson (2004) declared to be less satisfied with training opportunities and promotions than their full-time colleagues.

To sum up, the literature on the relationships between part-time work and labour productivity is ambiguous: both productivity-enhancing and reducing effects are plausible and so far we lack robust empirical results to gauge whether the net effect of part-time arrangements is positive or negative. Moreover, the available evidence suggests that female part-time work affects labour productivity negatively, but this evidence is mainly indirect and based on the observation of reduced training activity of part-time women.

Institutional factors

The final set of theories argues that pay differentials can be accounted for by analysing the institutions that underpin male and female part-time employment. Several studies have shown that part-timers are characterised by a lower level of union membership (Riley 1997) and are assumed to have lower bargaining power (Skåtun 1998). Negotiated overtime premia are a case in point: in most sectors unions have successfully lobbied for overtime premia for full-time employees exceeding contractually fixed working hours, while extra hours of part-time workers generally do not give rise to any overtime premium. Collective bargaining is likely to affect men and women differently given that unionization is typically stronger in predominantly male occupations/sectors. As a consequence, decentralisation of bargaining increases inter-sectoral pay differentials and gender/part-time wage penalties since women and part-timers are clustered in the same low-paying sectors (Teuling and Hartog, 1998).

Pay penalties for part-time workers and women have also been associated with firm-level decision-making structures that are often biased towards (male) full-time employees. The latter group enjoys privileged access to formal and informal information and power, which in turn leads to different career patterns and gender pay gaps (Grimshaw and Rubery 2001). In the broader perspective, female part-time work cannot be dissociated from the societal division of work based on stereotypical patterns: women still accomplish relatively more domestic (and almost always unpaid and low-status) work, while male roles involve more often commodified work and the pursuit of a career as 'bread-winner'.

Another factor is related to fiscal policies. Countries like Belgium, France, Germany and the UK promote part-time employment by subsidizing it through reduced social security contributions or tax relief which could lead to lower wage costs for employers. Also the composition of income and payroll taxes may influence the difference between full-time and part-time wages (Koskela and Schöb 1999). For instance, if income taxes are based on total annual income and the tax system is progressive, full-time employees have to be paid a higher gross hourly wage than part-time employees if both groups are to receive the same net hourly wage. Hence, trade unions bargaining for the same net hourly wage for all employees could be willing to accept higher gross hourly wages for full-time employees. The amount of payroll taxation, however, has the opposite effect given that in general per hour payroll taxes decrease with the number of hours worked.

Finally, the legislative context could influence the relationship between productivity and wages of women and part-time workers. In addition to fiscal policy, anti-discrimination laws, minimum wage legislation and institutionalised rights to request flexible working (in the UK introduced in 2003) may have a positive impact on the relative remuneration of both part-timers and women.

In light of the different theories reviewed in this section, the task of empirical research in this area should be to disentangle the relative importance of each of the different factors in explaining the gap between part-timers' and full-timers' productivity and wages. Unfortunately, the literature has so far not even firmly established whether such gaps actually exist.

Empirical evidence on productivity-wage gaps

The reason why the empirical literature still struggles to determine the precise magnitude of pay gaps is twofold. On the one hand, the studies on productivity effects of male and female part-time work we mentioned above do not compare productivity patterns with wage differentials. On the other hand, studies decomposing the wage gap between part-time and full-time workers do not include independent productivity measures. Instead, they rely on proxy variables such as education, occupation, sector of activity, experience, etc. which capture productivity differentials only imperfectly.

Bardasi and Gornick (2008), for instance, used micro-data for 1995 from the Luxembourg Income Study and find a significant part-time pay penalty for women in a cross-country comparison of Canada, Germany, Italy, Sweden, the UK and the US. But with the exception of Sweden, they conclude that much of these gaps should be attributed to different forms of segregation because worker and job controls substantially reduce the part-time pay penalty. Analogous results for the UK labour market can be found in Manning and Petrongolo (2008) who used pooled data from the Labour Force Survey from 2001 to 2003 to show that differences in the types of jobs and occupational segregation are the main factors associated with the hourly part-time pay penalty inflicted on British women. Hardoy and Schone (2006) used pooled data for 1997 and 1998 from the Norwegian Level of Living Surveys and recorded no hourly wage differences between female part-time and full-time jobs and no evidence of systematic selection bias after controlling for observed characteristics. Rodgers (2004) developed a cross-sectional analysis using the 2001 wave from the Household, Income and Labour Dynamics in Australia Survey and did not find significant hourly part-time pay gaps for Australian workers once selection into types of employment and worker and job characteristics were controlled for. Also Booth and Wood (2008), using panel data of the first four waves of the same survey (2001–2004), did not detect any part-time penalty in Australia. In fact, they observed the opposite: once unobserved individual heterogeneity was taken into account part-time women and men appeared to be paid a premium.

Hirsch (2005) used level and longitudinal estimates of wages from the US Current Population Survey (1995-2002) and also ascribed the largest share of the hourly part-time penalty to differences in worker and job characteristics; once full controls were included in the model, he found that the part-time pay gap was very modest at the beginning of individual careers. However, the part-time wage penalty was found to increase over time, a phenomenon that might reflect that part-timers accumulate lower levels of experience and human capital. Similar patterns were found by Russo and Hassink (2008), who used the pooled waves from 1999 and 2001 of the Working Conditions Survey for the Dutch labour market, and the study of career biographies of women from the UK by Connolly and Gregory (2010).

A very appealing way to avoid the problematic reliance on imperfect productivity proxies in these studies has been presented by Hellerstein et al (1999) and refined by Hellerstein and Neumark (2004) and others. In a nutshell, the authors used matched employer-employee data in order to simultaneously measure the contribution of women (and other groups of employees) to both added value and the firm's average wage (Section 4 presents the approach in more detail). Hellerstein et al. concluded that US women appear to be relatively less productive than their male colleagues, but also that this productivity difference is significantly smaller than the pay gap between men and women. In other words, women as a group appear to generate economic rents for their employers. Our study builds on Hellerstein et al.'s pioneering work but combines the estimation of the relative productivity and wages of women with the issue of part-time work, in particular the potential interaction between working time and gender. Indeed, no study we are aware of used accurate information on both wages and productivity in order to investigate whether part-time work generates economic rents and, a fortiori, whether part-time rents differ for men and women.

The case of Belgium

The development of part-time work in Belgium occurred earlier and affects a greater proportion of the labour force than in most OECD countries (OECD 2012). Some authors argued that the principle cause for this trend is not the feminization of the Belgian labour force per se, but rather economic crises and job shortages that have led employers and policy makers to propose part-time arrangements to women. Anecdotal evidence for this proposition is the discriminatory character of early part-time arrangements introduced in the 1980, such as the case of the Belgian firm Bekaert-Cockerill: in 1982, to face the problems encountered on its site in Fontaine-l'Evêque, the firm imposed mandatory part time on all female employees who were not household heads (Plasman 2007).

In 2011, the Belgian part-time rate as a percentage of total employment was 18.8 percent, a figure that is 2.2 percentage points higher than the OECD average. Belgium is not exceptional as regards the overrepresentation of women in part-time jobs. Indeed, in 2011 the proportion of women working less than full hours was 25.4 percentage points higher than the corresponding male rate of only 7 percent. As for segregation into occupations and sectors of activities, part-time workers in Belgium are overrepresented in elementary, service and craft occupations as well as in the manufacturing sector, hotels and restaurants, and the transport and telecommunications sector (Meulders and O'Dorchai 2009).

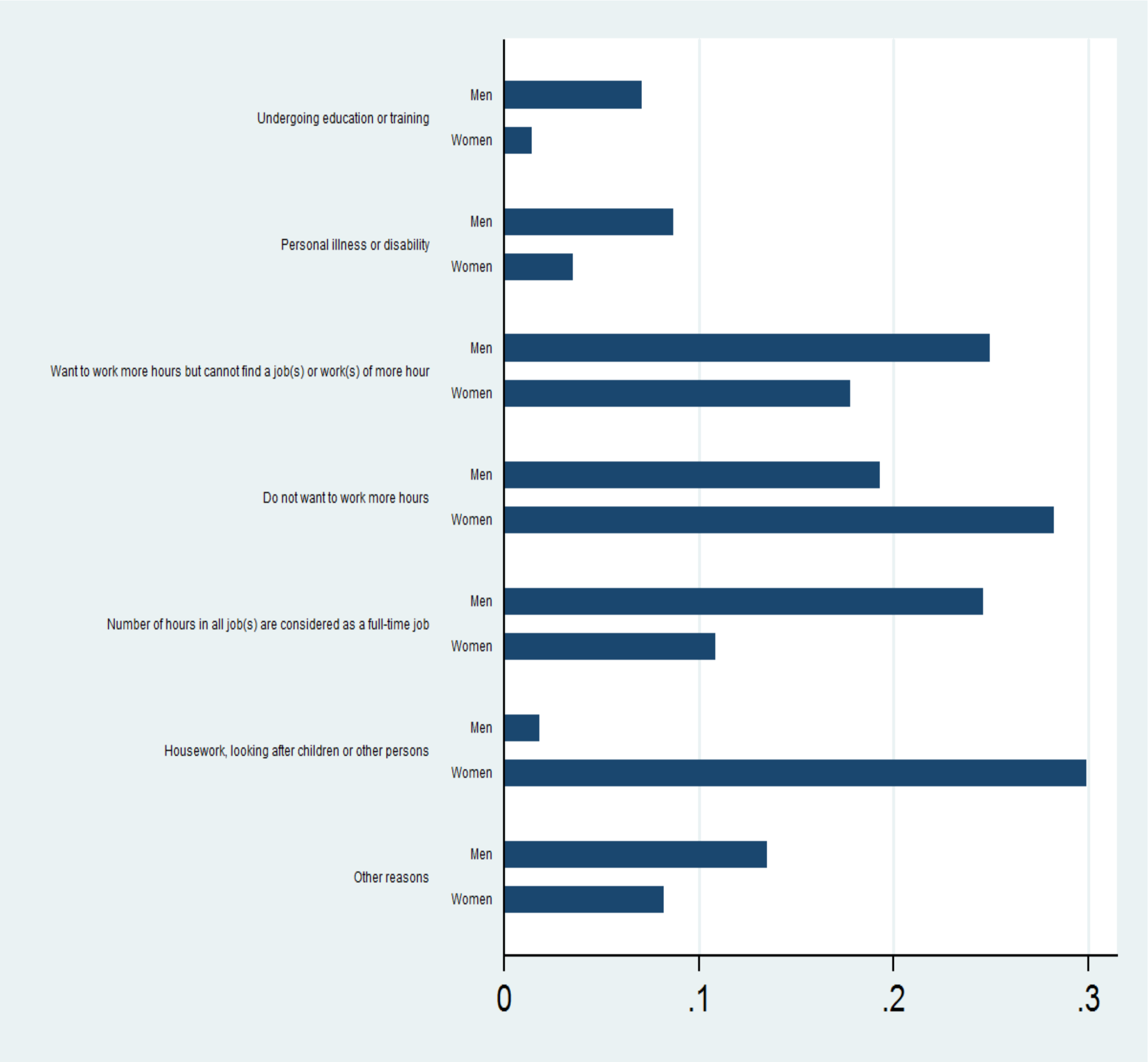
The regulation of part-time work in Belgium heavily relies on collective bargaining agreements at the national and sectoral level. These agreements cover all Belgian workers (i.e. their coverage rate is 100%). Unlike their counterparts in the United States, Belgian part-time workers are covered by unemployment insurance independently of the amount of hours worked. Benefits and other kinds of non-wage advantages are typically defined on a pro rata basis. Like in most countries, the progressivity of income tax encourages the reduction of working time in order to fall within lower tax brackets.

Some of the Belgian collective bargaining agreements incorporate explicit anti-discrimination rules. Meulders and O'Dorchai (2009) argued that Belgian labour law is more favourable to waged workers than the 1993 European Union Directive on working time allowing firms to opt out on certain elements of the Directive, such as the maximum number of weekly working hours. Unsurprisingly, in June 2008 Belgium voted against the application of this opt-out clause in the Council of Ministers of the EU. Belgium's antidiscrimination policies compare favourably with EU Member States and the country is considered a 'good European pupil' (Institute for the equality of women and men, 2010; p. 71).

Similar to related work on other countries cited above, empirical studies on Belgium suggest that pay penalties associated with part-time work and gender are correlated with individual and firm characteristics. Jepsen (2001) and Jepsen et al. (2005) used data on the 1990s from the Household Panel Survey and the Structure of Earnings Survey, respectively, and concluded that the pay difference between part- and full-time women is accounted for by observable characteristics. O'Dorchai et al. (2007) found that male part-timers were paid 24 percent less per hour than male fulltimers, but only 28 percent of this difference was left unexplained by observables in their Oaxaca-Blinder decomposition. Jepsen (2001) found that only 13.7 percent of the full-time gender pay gap remained after introducing observable characteristics. The above-mentioned shortcoming of Oaxaca-Blinder-type decompositions of course also applies to extant studies on Belgium: in the absence of an independent productivity measure, observable characteristics only 'explain' observed part-time wage gaps if they are correlated with labour productivity.

The productivity effects of part time are likely to depend on the motives that lead individuals to reduce working hours; if men and women reduce working hours for different reasons, we might observe a gender bias in the productivity effects of part-time work. Anxo et al. (2002), for instance, showed that the presence of children is among the chief determinants of women's working hours. A representative picture of part-time motives for Belgian men and women can be found in the European Union Statistics on Income and Living Conditions (EU-SILC), Eurostat's EU-wide panel survey, which among many other job-related variables includes the item "reason for working less than 30 hours per week". Figure 1 shows the results for the Belgian sample for the period 2008-2010. Comparing the answers of 436 men and 2,453 women working less than 30 hours reveals a clear gender bias: the most frequent reason for female part-time work is “Household work, looking after children or other persons” (29.9 percent of female responses), followed by “Do not want to work more” (28.3 percent). The most frequent responses for men are “Want to work more hours but cannot find a job(s) or work(s) of more hours“ (25 percent) and “Number of hours in all job(s) are considered as full-time job” (24.5 percent). Moreover, 7.1 percent of men state to work in part-time positions due to training or education activities, against only 1.4 percent of women. In Section 5 we show how these response patterns can be linked to our empirical findings.

Figure 5.1 – Reasons for working less than 30 hours per week



Source: Belgian sample of EU-SILC panel, 2008-2010.

3. Data and descriptive statistics

Our empirical analysis is based on a combination of two large data sets spanning the period 1999-2010. The first is the Structure of Earnings Survey (SES). It covers all firms operating in

Belgium that employ at least 10 workers and with economic activities within sections C to K of the NACE nomenclature (Rev. 1). The survey contains a wealth of information, provided by the human resource departments of firms, both on the characteristics of the latter (e.g. sector of activity, number of workers, level of collective wage bargaining) and on the individuals working there (e.g. age, education, tenure, gross earnings, paid hours, gender, occupation, etc). The SES provides no financial information. Therefore, it has been merged with a firm-level survey, the Structure of Business Survey (SBS). The SBS provides information on financial variables such as firm-level added value and gross operating surplus per hour. The coverage of the SBS differs from the SES in that it does not include the whole financial sector (NACE J) but only Other Financial Intermediation (NACE 652) and Activities Auxiliary to Financial Intermediation (NACE 67). The data collection and merger of the SES and SBS datasets has been carried out by Statistics Belgium using firms' social security numbers.

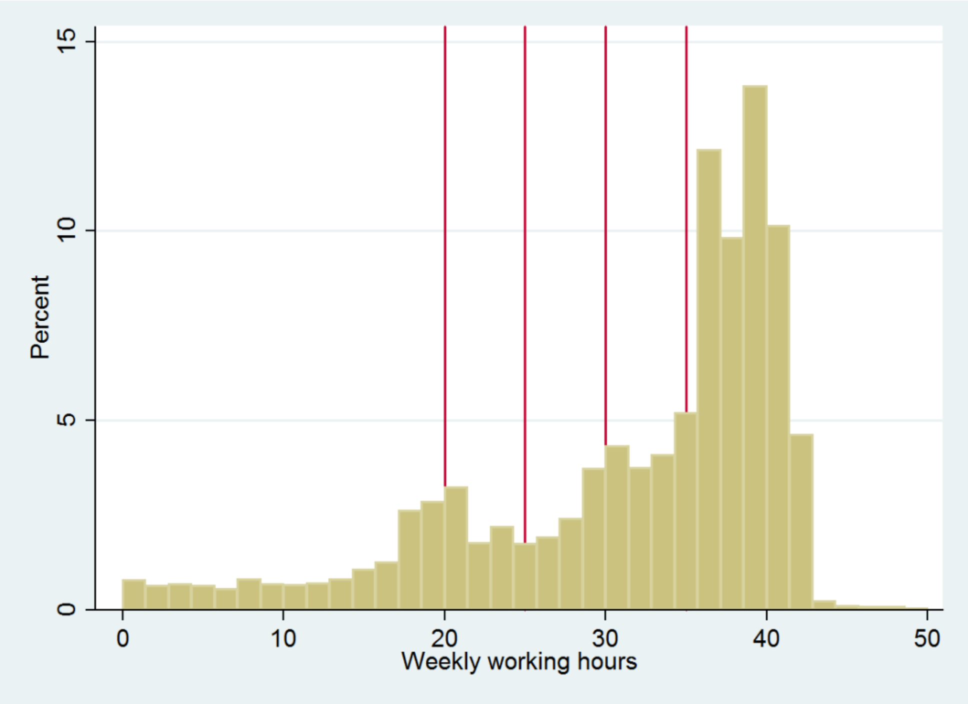
Our final sample (used in the difference Generalized Method of Moments (GMM) specification, see below) consists of an unbalanced panel of 1,430 firms and 128,006 individuals, yielding 5,171 firm-year-observations during the 12 year period (1999-2010). It is representative of all medium-sized and large firms employing at least 10 employees within sections C to K of the NACE Rev. 1 nomenclature, with the exception of large parts of the financial sector (NACE J) and almost the entire electricity, gas, and water supply industry (NACE E).

Our earnings measure corresponds to total gross wages, including premia for overtime, weekend or night work, performance bonuses, commissions, and other premia. Work hours represent total effective remunerated hours in the reference period (including paid overtime hours). The firm's added value per hour is measured at factor costs and based on the total number of hours effectively worked by the firm's employees. All variables in the SES-SBS are provided by the firm's management and therefore more precise compared to self-reported employee or household surveys.

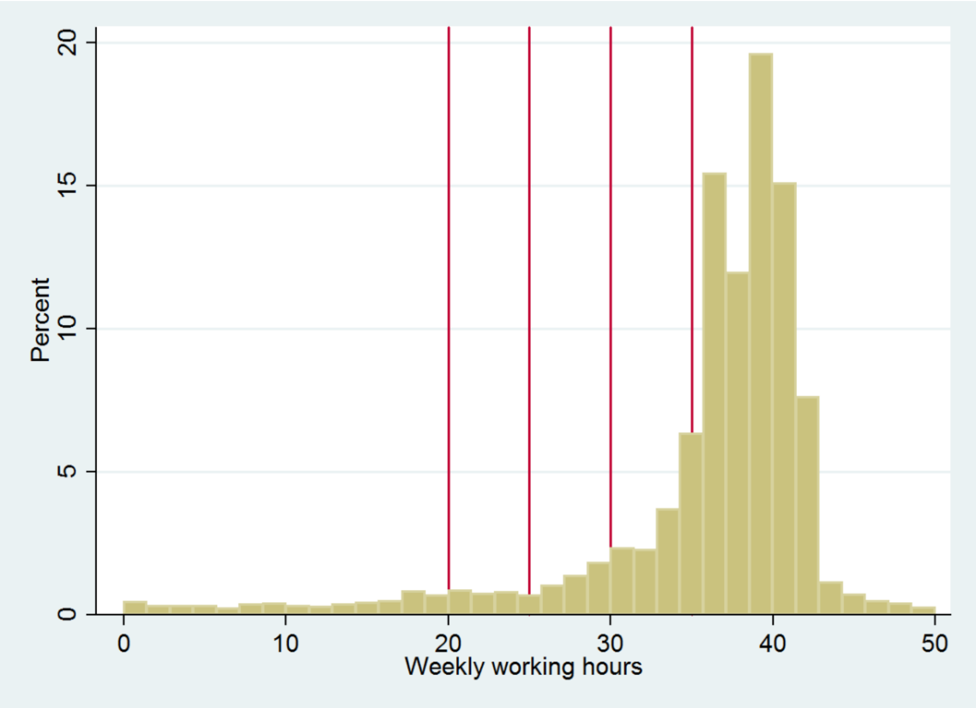
It is standard practice to define part-time work with reference to the national benchmark of full-time working hours (ILO Part-Time Work Convention No. 175 from 1994; Bardasi and Gornick 2008; Manning and Petrongolo 2008). In Belgium, national collective agreements fix maximum working time at 38 hours per week and 8 hours per day. These thresholds are renegotiated by social partners in most industries and/or firms so that actual statutory maximum working hours are often closer to 35 hours per week and 7 hours per day (Meulders and O'Dorchai 2009). Working hours exceeding these thresholds are typically treated as overtime. In our data, the 35-hour mark clearly stands out as threshold separating the bulk of 'normal' full-time employments from the rest of the workforce (see vertical lines in panels a (women) and b (men) of Figure 2) and we therefore define part-time work as involving less than 35 hours per week (cf. Rodgers 2004; Booth and Wood 2008).

FIGURE 5.2 – Distribution of individuals according to weekly working hours (1999-2010)

a) Women



b) Men



Notes : Data source: SES-SBS 1999-2010. Vertical lines represent 20, 25, 30 and 35 hours per week.

Past research highlights considerable heterogeneity among part-time workers (Hirsch 2005; Russo and Hassink 2008). For instance, the repercussions of part-time arrangements are likely to differ according to whether the individual is absent during much of the work week (e.g. an employee with peripheral tasks coming in only one or two days per week) or whether she is almost working full-time (e.g. an employee who works similarly to her full-time colleagues during the entire week but leaves the office on Friday noon). Panel a of Figure 2 is a quantitative illustration of the heterogeneity of female part-time work: the distribution has two local peaks around 20 and 30 hours per week. In the absence of an obvious threshold to distinguish 'short' from 'long' part-time jobs, we used three different limits for short part-time jobs: 20, 25 and 30 hours (see Section 4.3). We therefore distinguish between three groups: workers with up to 20/25/30 hours (short part-time); between 20/25/30 and 35 hours (long part-time); and 35 or more working hours per week (full-time jobs).

Table 5.1 – average GROSS hourly wages (1999-2010)

	Men	Women	*(Wage men – wage women)/ wage women*
Full-time jobs (FT)	16.57 euros	14.98 euros	*0.11*
Long part-time jobs (LPT)	14.79 euros	13.79 euros	*0.07*
(Wage FT – wage LPT) / wage LPT	*0.12*	*0.09*	
Short part-time jobs (SPT)	14.30 euros	11.88 euros	*0.20*
(Wage FT – wage SPT) / wage SPT	*0.16*	*0.26*	

Notes: Constant 2004 euros deflated with CPI.

Short part-time jobs: [0;25[; long part-time jobs [25;35[.

Using 25 hours as threshold for short part-time work, the Belgian SES wage data yields an average wage gap between full-time men and women of 11 percent during the 2000s (see Table 1). The gender wage gap among workers with short and long part-time jobs was 7 and 20 percent, respectively. We also observe wage penalties linked to working time: women with long part-time jobs earn 9 percent less than female fulltimers, whereas the penalty for short part-timers is 26 percent. The corresponding wage penalties among men are 12 and 16 percent, respectively.

Table 5.2 – Descriptive statistics at the firm and individual level (mean values for 1999-2010)

Variables:	Firm level	Individual level			
		Total	Full-time jobs[1]	Long part-time jobs[2]	Short part-time jobs[3]
Ln (added value per hour), constant 2004 euros	3.78	3.81	3.86	3.76	3.63
Ln (hourly wage), constant	2.79	2.76	2.79	2.69	2.66
Pay hours per week	1097.0	35.4	39.4	31.1	16.2
Full-time (%)[1]	76.8				
Long part-time jobs (%)[2]	17.6				
Short part-time jobs (%)[3]	5.5				
Women (%)	22.0	22.4	18.5	27.6	38.9
Workers < 40 years (%)	52.1	51.6	53.3	48.5	45.3
Workers >= 40 years (%)	47.9	48.5	46.7	51.5	54.7
Education level 1 (ISCED 1	32.5	34.2	30.4	41.8	46.4
Education level 2 (ISCED 3	41.6	41.2	39.6	45.2	44.2
Education level 3 (ISCED 5, 6	25.9	24.6	30.1	13.0	9.5
Workers with fixed-term	3.8	4.5	4.0	4.3	8.2
Managers (%)	4.0	3.7	4.9	1.3	0.9
Professionals (%)	10.9	10.3	13.6	4.1	2.6
Technicians and ass.	8.2	7.9	9.8	4.5	3.0
Clerical occupations (%)	14.9	14.6	16.3	12.7	12.4
Craft (%)	25.4	25.3	23.4	31.8	27.6
Machine operators (%)	25.5	26.7	22.7	32.6	29.2
Service (%)	2.6	2.7	2.3	1.7	5.8
Elementary occupations (%)	8.5	8.9	6.9	11.3	18.5
Firm size (number of workers)	459.7	749.2	739.8	799.4	717.8
Mining and quarrying (%)	0.00	0.4	0.4	0.3	0.2
Manufacturing (%)	62.3	63.5	62.7	69.4	58.2
Electricity, gas and water	0.00	0.1	0.1	0.0	0.0
Construction (%)	13.2	10.9	11.8	8.6	9.3
Wholesale and retail trade (%)	7.2	7.0	7.0	7.4	5.8
Hotels and restaurants (%)	1.3	1.0	1.0	0.8	2.1
Transport, storage and	6.1	8.0	7.6	7.7	11.7
Financial intermediation (%)	1.1	0.8	0.9	0.8	0.6
Real estate, renting and	8.3	8.3	8.7	5.0	12.1
Number of individual		128,006	89,875	25,066	13,065
Distribution in %		100	70.2	19.6	10.2
Number of firm-year-	5,171				

Notes: [1] Full-time jobs: >= 35 work hours per week. [2] Long part-time jobs: >= 25 & < 35 work hours per week. [3] Short part-time jobs: < 25 work hours per week.

Table 5.2 sets out the means of selected variables both at the firm and individual level. At the firm level, the average share of fulltimers is 76.8 percent, the shares of short and long part-time employment are 5.5 and 17.6 percent, respectively. Moreover, 22 percent of hours are worked by women; 52.1 percent by workers younger than 40 years; and 3.8 percent by people on fixed-term contracts.

At the individual level, we observe a positive relationship between working time and the hourly added value of the firm in which the individual is employed. The group of full-time workers contains a higher share of individuals below 40 years (53.3) compared to short and long part-time jobs; the distribution of educational credentials is positively related with the length of the working week, with women being better educated than men in our sample (34 percent have reached ISCED levels 5, 6 or 7 compared to only 22 percent of men). The incidence of fixed-term work contracts is similar among full-time and long part-time workers (around 4 percent), but twice as high among short part-timers.

In several occupations full-time jobs clearly predominate, namely managers, professionals and technicians. By contrast, the proportion of part-time employment among elementary occupations is considerably higher. The distribution of working time is highly gendered, so that the information in Table 2 can be complemented with figures on the occupational distribution and working regimes by gender (see Appendix A). For instance, the share of clerical occupations among male fulltimers is 10.6 percent and decreases to 4.4 among part-timers; female clerks, however, represent a higher share of full-time jobs (40.1 percent), but also remain the biggest group among long and short part-time jobs. Crafts and machine operators are more evenly distributed with respect to working time, but these occupations are much more frequent among male workers. The opposite holds for service and elementary occupations: the share of these groups is higher among women and represents respectively 9.1 and 23.5 percent of all female short part-time hours.

As to the distribution of working time regimes across sectors of activity, fulltimers are overrepresented in the construction sector, whereas long part-time jobs are overrepresented in manufacturing. Short part-time work is overrepresented in hotels and restaurants, services (real estate, renting and business activities) and transport, storage and communication. The distribution across sectors and working regimes differs among men and women (Appendix A). Men are more concentrated in manufacturing and construction, two sectors that also provide the bulk of male part-time jobs; we find higher shares of women in wholesale and retail, transport, storage and communication as well as real estate, renting and business activities. The latter concentrates 22.2 percent of all short part-time hours worked by women (compared to only 5.8 percent for men).

4. Models and estimation results

Model 1 - Shares of part-time and female workers

Table 5.3 shows GMM-DIFF estimates of (baseline) Model 1. The figures in column (3) are estimated with (the logarithm of) the difference between the firm's hourly added value and average wage as dependent variable, columns (1) and (2) are obtained with (the logarithm of) the firm's added value per hour and its average hourly wage as dependent variable, respectively. All models have a good fit and pass the Chi-square test. All equations also pass the statistical tests for underidentification, weak identification and overidentification. In addition, we find that the null hypothesis that the shares of part-time and female workers are exogenous can be rejected both in the value-added and productivity-wage gap equations. In the wage regression, the p-value associated to the endogeneity test is equal to 0.12. Results for the wage equation based on first-differences without instrumenting (available on request) confirm the negative wage effect for women (the significant coefficient is -0.20) and suggest a significant but small negative wage effect for part-timers (-0.03).

Table 5.3 – Difference GMM estimates, baseline specification (model 1)

	(1) Added value per hour (ln)	(2) Mean hourly wage (ln)	(3) Added value-wage gap (ln)
Share of part-time workers	0.08*	-0.01	0.09*
Share of female workers	0.02	-0.11***	0.12**
Control variables:			
Share of workers < 40 years	0.05	-0.14***	0.19***
Share of workers with fixed contract	0.10**	0.04	0.06
Education level 2 (ISCED 3 and 4)	-0.03	-0.00	-0.03
Education level 3 (ISCED 5, 6 and 7)	-0.10**	0.10***	-0.19***
Managers	-0.14	0.55***	-0.68***
Professionals	0.04	0.19***	-0.15*
Technicians and ass. professionals	-0.04	0.06**	-0.10
Clerical occupations	-0.04	0.09***	-0.13**
Craft	-0.03	-0.07***	0.04
Machine operators	-0.02	-0.07***	0.05
Elementary occupations	-0.03	-0.08***	0.06
Capital stock	-0.00	0.00	0.00
Firm size	0.00*	0.00	0.00*
Squared firm size	-0.00	0.00	-0.00*
Number of firm-year-observations	5,171	5,171	5,171
Underidentification test			
p-value Kleibergen-Paap rk LM	0.00	0.00	0.00
Weak identification test			
Kleibergen-Paap rk Wald F statistic	447.29	477.13	831.47
Overidentification test			
p-value of Hansen J statistic	0.48	0.50	0.35
Endogeneity test of endogenous			
p-value	0.03	0.12	0.01

Notes: ***/**/* significant at the 1, 5 and 10% level. All models include year dummies and control for the firm's sector of activity at NACE 1. Part-time jobs < 35 hours per week. Reference categories include respectively the share of full-time workers, the share of male workers, the share of workers >= 40 years, the Education level 1 (ISCED 1 and 2) and service occupations. First two lags of main explanatory variables are used as instruments.

Estimates for the control variables reflect other findings in the literature. For instance, relative to the reference category (i.e. the share of workers that are 40 years or older), a higher share of younger workers is negatively related with the firm's hourly wage: relative to the group of elderly workers, an increase of one percentage point in the share of young workers decreases hourly wages by around 0.14 percent (i.e. 0.14*0.01 = 0.0014 = 0.14 percent), whereas young workers have no significant impact on added value. The combined result of these two effects is shown in the third column, i.e. the coefficients explaining the gap between added-value and hourly wage. The significant coefficient of 0.19 indicates that a relative increase in the share of younger workers generates on average a positive rent for the firm, corroborating similar results for Belgium found by Cataldi et al. (2012). Estimates regarding the firm's occupational mix also mirror earlier findings that occupations are associated with significant rents (Gottschalk 1978; Kampelmann and Rycx, 2012): while the firm's occupational composition has a significant impact on the average wage, no similar pattern emerges in the added-value equation – in fact, the productivity coefficients for occupations do not display any significant difference relative to the respective reference groups (service occupations).

Regarding the firm's share of part-time workers, three important results emerge from Table 5.3. First, we observe that the length of the working week matters for firm productivity: relative to the reference category of fulltimers, a one percentage point change in the share of part-timers is associated with a 0.08 percent change in the firm's productivity. Second, the firm's composition in terms of different working time regimes seems to be unrelated to the average hourly wage: the part-time wage coefficient is statistically insignificant. This corroborates findings by Jepsen (2001) and Jepsen et al. (2005) that part-time work in Belgium is not associated with significant pay penalties once we control for variables like gender, education, occupation and sectors of activity. Third, our results regarding the gap between added value and average wages suggest that an increase in the group of part-time workers generates positive rents for the average employer (the significant coefficient equals 0.09).

Table 5.3 further shows that women as a group are also associated with economic rents (the significant coefficient in the gap equation is 0.12). But the origin of these rents is different compared to the effect of part-time work: they do not stem from higher productivity relative to the reference group (men), but from a significantly negative impact on the firm's hourly wage. This is in line with estimations by Jepsen (2001), who found a negative price effect for women in the Belgian labour market, but differs from those of Vandenberghe (2011) who rejected the hypothesis of gender wage discrimination.

Model 2 - Distinction between long and short part-time jobs

Our second model allows for the part-time effect to differ between 'short' and 'long' part-time jobs. In the absence of any obvious upper threshold for short part-time work, Table 4 shows results for three alternative thresholds: 20 (Model 2.1), 25 (Model 2.2) and 30 weekly working hours (Model 2.3). The added-value and gap equations in all three models pass all four statistical tests, suggesting that our instrumental variables approach is both warranted and valid. In contrast, results suggest that the shares of part-time and female workers are not endogenous in the wage regressions. Yet, estimates obtained for the wage equations with the first-difference estimator (available on request) are not substantially different from those reported in Table 5.4.

Table 5.4 –Difference GMM estimates, distinguishing short and long part-time (model 2)

	Model 2.1 Part-time thresholds: 0-20/20-35/35			Model 2.2 Part-time thresholds: 0-25/25-35/35			Model 2.3 Part-time thresholds: 0-30/30-35/35		
	(1) Added value per hour (ln)	(2) Mean hourly wage (ln)	(3) Added value-wage gap (ln)	(4) Added value per hour (ln)	(5) Mean hourly wage (ln)	(6) Added value-wage gap (ln)	(7) Added value per hour (ln)	(8) Mean hourly wage (ln)	(9) Added value-wage gap (ln)
Share of short part-time workers	-0.21	0.04	-0.20	-0.10	0.03	-0.11	0.09	-0.02	0.12
Share of long part-time workers	0.11**	0.01	0.11**	0.12**	0.00	0.12**	0.08*	0.02	0.07
Share of female workers	0.02	-0.11***	0.13**	0.03	-0.11***	0.13***	0.01	-0.11***	0.12**
Control variables:									
Share of workers < 40 years	0.04	-0.14***	0.19***	0.05	-0.14***	0.19***	0.05	-0.14***	0.19***
Share of workers with fixed contract	0.09*	0.06**	0.06	0.10*	0.06**	0.06	0.10*	0.05*	0.06)
Education level 2 (ISCED 3 and 4)	-0.03	0.00	-0.03 (0.04)	-0.03	0.00	-0.03	-0.03-0.0304	-0.00	-0.03
Education level 3 (ISCED 5, 6 and 7)	-0.10**	0.10***	-0.20***	-0.10**	0.10***	-0.19***	-0.09**	0.10***	-0.19***
Managers	-0.14	0.52***	-0.68***	-0.14	0.52***	-0.68***	-0.14	0.53***	-0.68***
Professionals	0.03	0.18***	-0.14*	0.03	0.18***	-0.14*	0.03	0.18***	0.15*
Technicians and ass. professionals	-0.04	0.04*	-0.09	-0.05	0.04*	-0.10	-0.04	0.05*	-0.09
Clerical occupations	-0.05	0.08***	-0.14**	-0.05	0.08**	-0.14**	-0.04	0.05*	-0.13*
Craft	-0.04	-0.08***	0.03	-0.04	-0.08***	0.03	-0.03	-0.08***	0.05
Machine operators	-0.03	-0.09***	0.04	-0.03	-0.08***	0.04	-0.02	-0.08***	0.04
Elementary occupations	-0.03	-0.09***	0.04	-0.04	-0.09***	0.04	-0.02	-0.09***	0.06
Capital	0.00	0.00	0.00	0.00	-0.00	0.00	0.00	-0.00	0.00
Firm size	0.00*	0.00	0.00*	0.00*	0.00	0.00*	0.00*	0.00	0.00*
Squared firm size	-0.00*	0.00	-0.00*	-0.00	0.00	-0.00*	-0.00	0.00	-0.00*
Number of firm-year-observations	5,171	5,171	5,171	5,171	5,171	5,171	5,171	5,171	5,171
Underidentification test									
p-value Kleibergen-Paap rk LM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Weak identification test									
Kleibergen-Paap rk Wald F statistic	42.47	42.47	42.47	63.38	63.38	63.38	119.09	119.09	119.09
Overidentification test									
p-value of Hansen J statistic	0.70	0.05	0.58	0.72	0.08	0.49	0.52	0.21	0.65
Endogeneity test									
p-value	0.03	0.73	0.04	0.03	0.49	0.04	0.07	0.18	0.03

Notes: ***/**/* significant at the 1, 5 and 10% level. All models include year dummies and control for the firm's sector of activity at NACE 1. Reference categories include respectively the share of full-time workers, the share of male workers, the share of workers >= 40 years, the Education level 1 (ISCED 1 and 2) and service occupations. First two lags of main explanatory variables are used as instruments.

The results for Model 2 corroborate the conclusion of Model 1 regarding the share of female workers: the combination of a significantly negative wage effect and the absence of a productivity difference with respect to the share of male workers suggests that female workers as a group are associated with significant economic rents. The corresponding gap coefficient hardly varies between Models 2.1, 2.2 and 2.3.

Model 2 confirms the above result that part-time workers appear to be more productive relative to fulltimers and that after controlling for observed and firm fixed unobserved characteristics part-time employment is not associated with differences in pay. However, the distinction between short and long part-time work allows pinpointing this effect: all three variations of Model 2 converge in suggesting that the positive impact on productivity is only associated with long part-time jobs – no productivity effect is observed for short part-time work. Models 2.1 and 2.2 further indicate that long part-time is associated with significant economic rents. In Model 2.3 these rents are also positive but not significant (p-value = 0.15), a result that suggests that the threshold of 30 hours is probably too high to capture rent differences between full-time and long part-time jobs.

Model 3 - Interactions between gender and part-time shares

Model 3 further refines the analysis by allowing for the effect of short and long part-time work to differ between men and women. While adding interaction variables generally comes at the cost of decreasing the precision with which each effect is measured (Göbel and Zwick, 2012), results for Model 3 corroborate Model 2: the positive productivity effect of part-time work continues to be associated with long rather than short part-time; and both long part-time jobs and the group of women are associated with significant economic rents (see Table 5.5). But Model 3 also yields additional insights. Firstly, the positive productivity effect of long part-time appears only for the subgroup of male long part-time workers but not for women. Secondly, we observe contrasting wage profiles for women and men. While for men a shorter week is associated with a (slight and not always significant) increase of the firm's hourly wage, for women we observe wage penalties that are inversely related to the length of the working week: in Model 3.1 (based on a threshold for short part-time jobs of 20 weekly working hours), the negative wage coefficients for female full-time, long part-time and short part-time work are -0.11, -0.18 and -0.25, respectively. Women thus accumulate the negative wage effects associated with their gender and with working fewer hours. Finally, the profiles for the gap equation suggest that female full-timers and the group of long part-time workers are associated with employer rents. These rents have different origins according to gender: for male long part-timers the origin lies in their relatively higher productivity, for female long part-timers and full-timers they can be attributed to the relatively lower pay of these groups. For one of the three variants of Model 3 we also observe significant negative rents (from the employer perspective) associated with male short part-time work, but this result is somewhat unstable.

Table 5.5 –Difference GMM estimates, distinguishing short and long part-time with gender interaction (model 3)

	Model 3.1 Part-time thresholds: 0-20/20-35/35+			Model 3.2 Part-time thresholds: 0-25/25-35/35+			Model 3.3 Part-time thresholds: 0-30/30-35/35+		
	(1) Added value per hour (ln)	(2) Mean hourly wage (ln)	(3) Added value-wage gap (ln)	(4) Added value per hour (ln)	(5) Mean hourly wage (ln)	(6) Added value-wage gap (ln)	(7) Added value per hour (ln)	(8) Mean hourly wage (ln)	(9) Added value-wage gap (ln)
Share of female full-time workers	0.09	-0.11***	0.20***	0.09	-0.11***	0.20***	0.09	-0.11***	0.20***
Share of male long part-time workers	0.12**	0.03	0.10*	0.14**	0.02	0.12*	0.20**	0.00	0.19**
Share of female long part-time	0.12	-0.18***	0.31**	0.11	-0.16**	0.30*	0.13	-0.15*	0.32
Share of male short part-time	-0.27	0.09	-0.32*	-0.12	0.07*	-0.18	-0.10	0.07*	-0.15
Share of female short part-time	-0.03	-0.25**	0.23	0.07	-0.19**	0.26	0.06	-0.19**	0.25
Control variables:									
Share of workers < 40 years	0.04	-0.15***	0.18***	0.04	-0.14***	0.19***	0.04	-0.14***	0.18***
Share of workers with fixed contract	0.08*	0.05**	0.04	0.09*	0.06**	0.04	0.09*	0.06**	0.04
Education level 2 (ISCED 3 and 4)	-0.03	-0.00	-0.03	-0.03	0.00	-0.03	-0.03	0.00	-0.03
Education level 3 (ISCED 5 and 6)	-0.09**	0.10***	-0.18***	-0.09**	0.10***	-0.18***	-0.09**	0.10***	-0.19***
Number of firm-year-observations	5,171	5,171	5,171	5,171	5,171	5,171	5,171	5,171	5,171
Underidentification test									
p-value Kleibergen-Paap rk LM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Weak identification test									
Kleibergen-Paap rk Wald F	25.1	25.1	25.1	28.3	28.3	28.3	10.9	10.9	10.9
Overidentification test									
p-value of Hansen J statistic	0.73	0.12	0.54	0.73	0.22	0.57	0.73	0.23	0.60
Endogeneity test									
p-value	0.09	0.77	0.06	0.08	0.78	0.08	0.07	0.88	0.04

Notes: ***/**/* significant at the 1, 5 and 10% level. All models include year dummies and control for the firm's sector of activity at NACE 1. Reference categories include respectively the share of male full-time workers, the share of workers >= 40 years, the Education level 1 (ISCED 1 and 2) and service occupations. First two lags of main explanatory variables are used as instruments. Regressions control for firm composition in terms of occupations and educational attainment.

5. Conclusion

The results presented in this chapter mark three incremental steps. Model 1 provides separate estimates for the effects of the firm's shares of part-time workers and women. Findings suggest that both characteristics are related to employer rents, but also that these rents are generated through different mechanisms. In the case of part time, the gap between added value and wages per hour is related to a higher productivity relative to the group of fulltimers. By contrast, the rents from female workers appear to be driven by the relatively low pay of this group.

Model 2 introduces the distinction between short and long part-time work and enables us to pinpoint the productivity of part-time work: results indicate that it is long and not short part-time jobs that are linked to higher added value per hour. This finding is in line with theories that emphasize a positive effect of part-time employment on labour productivity (Section 2.1.3), but we are not aware of an explicit theory that accounts for the hump-shaped productivity profile we document in this paper: starting with low productivity and low working hours, labour productivity first increases with the length of the work week but then decreases once the full-time threshold (35 hours) is reached. As a consequence, it appears that above a certain threshold, variously 20, 25 or 30 hours, certain negative aspects of part-time jobs (start-up costs, coordination problems, lower accumulation of human capital, etc) are more than off-set by positive effects (management of fluctuations, longer opening hours, etc). The idea that the observed pattern is driven by a combination of overlapping factors is in line with the fact that our results are insensitive to the exact threshold defining short and long part-time jobs.

Model 3 allows for the effect of short and long part-time work to differ among men and women. Despite the higher number of interaction variables in the model, results tend to corroborate the finding of economic rents associated with the shares of both women and long part-timers. In fact, we find a positive gap between the added-value and wage effect for female full-timers and both male and female long part-timers, but the origin of these gaps differ: for the group of male workers in long part-time jobs it is related to increases in firm productivity without increasing hourly wages, while changes in the share of female full-timers and long part-timers are associated with lower wages without decreasing productivity.

Our findings underline the importance of including a gender dimension in the analysis of part-time work. Model 3 provides evidence that women's lower pay is tightly related to their involvement in part-time work: the shorter the working week, the higher is the wage penalty inflicted on women. But this means that there is a gender effect because male part-timers do not appear to suffer pay losses. A relevant analytical question is therefore how working less-than-normal working hours yields different outcomes for men and women.

We argue that part of the answer is provided by indirect evidence that a) men and women typically do not have the same motives for working in part-time jobs; and b) that the opportunity structure in terms of availability and types of part-time jobs differs among men and women.

Regarding the motives for reduced hours, Section 2.3 provides some evidence that male workers are more likely to use part-time positions to engage in training (and many men want to work longer hours), whereas women put forth domestic duties as the main rationale for working reduced hours (and many women declare not to want to increase hours). These motives could be related to the qualification and motivation of employees and therefore at least partly account for the higher productivity and wages of male part-timers. It should be noted however, that the EU-SILC data on motives for part

But individual motives can only be a partial explanation given that they necessarily interact with the opportunity structure in which men and women operate. Male part-time employment is concentrated in certain capital-intensive and unionized sectors (manufacturing, construction) and occupations (crafts, machine operators), and EU-SILC data suggest that relatively more men consider their part-time jobs to be full-time jobs. In Belgium and other European countries with similar gender differences in the employment structure, it is therefore plausible that numerous part-time jobs in predominantly male occupations and industries are likely to be the result of collectively negotiated reductions in working hours. Circumstantial evidence suggests that these arrangements are often accompanied with corresponding changes in workplace design but not with reductions in hourly pay rates.

This contrasts with female part-time employment whose predominance in service occupations and sectors means that hours reductions are less likely to be the result of collective bargaining. Moreover, as Connolly and Gregory (2008) showed for the UK, women switching from full- to part-time employment often do so at the expense of occupational downgrading and the loss of firm-specific skills, especially if the employer provides few part-time positions so that women are forced to switch firms in order to reduce hours. Female part-time employment is therefore more likely to be the result of individual reductions of working hours that are associated with significantly lower wages (without being less productive). It should, however, be noted that the distribution of men and women across different working hours and occupations/sectors is not clear-cut. For instance, if long part-time work is the result of collectively bargained working time reductions in certain occupations (crafts, machine operators) or sectors (manufacturing), this will affect the women and men employed in short or long part-time jobs in these occupations /sectors in a similar way.

While an interpretation of our results in terms of a gender bias in the motives for and the opportunity structure of part-time jobs is therefore plausible, it should be noted that our evidence for this interpretation is essentially indirect. Future research in this area could test these interpretations with more detailed data on the motives of male and female part-time work differentiating short and long part-time work (the Belgian SILC sample we used in this paper is too small to allow for robust inferences) and more direct evidence on whether the workplace design differs along the dimensions of gender and (long and/or short) part-time work, for instance through qualitative observations within firms.

Although our findings suggest that beyond around 25 weekly working hours both male and female part-time work gives rise to employer rents, the welfare implications for men and women are quite different: compared to full-timers, male part-timers do not reap the full benefits of productivity increases but their hourly pay rates do not suffer from this. In contrast, while female part-time work does not affect productivity, it is more likely to generate precarity due to the combination of fewer working hours and lower hourly wages.

A challenge for future research in this area is to analyse in more detail the interplay between gender-related differences in individual motives and opportunity structures, for instance by combining data on individual biographies (such as the surveys used by Connolly and Gregory 2008) with firm-level data on productivity and labour force composition (such as the matched employer-employee data used in this paper).

PART III –
At-risk group: workers with human capital lacunae

CHAPTER 6 - The importance of human capital in boosting productivity and wages

1. Introduction

Surprisingly, most economists with an interest in human capital have neglected the level of the firm to study the education-productivity-wage nexus. And the few published works considering firm-level evidence are lacking a proper strategy to cope with the endogeneity problem inherent to the estimation of production and wage functions. This chapter taps into a rich, firm-level, Belgian panel database that contains information on productivity, labour cost and the workforce's educational attainment. It aims at providing estimates of the causal effect of education on productivity and wage/labour costs. Therefore, it exclusively resorts to within firm changes to deal with time-invariant heterogeneity bias. What is more, it addresses the risk of simultaneity bias (endogeneity of firms' education-mix choices in the short run) using the structural approach suggested by Ackerberg, Caves & Frazer (2006), alongside more traditional system-generalized method of moments (GMM) methods (Blundell & Bond, 1998) where lagged values of labour inputs are used as instruments. Results suggest that human capital, in particular larger shares of university-educated workers inside firms, translate into significantly higher firm-level labour productivity, and that labour costs (and thus wages) are relatively well aligned on education-driven labour productivity differences. This result has booth theoretical and policy implication. From a theoretical point of view, the result constitue a validation of the he Mincerian assumption that more education and higher individual wages is driven by a strong positive link between education and firm-level productivity. More in terms of policy, it suggests that more educated individuals contribute positively to firm productivity which in turn are able to pay higher wage. This should confort those who think that the ongoing expansion of education, mainly via the massification of tertiary education is a durable source of prosperity.

There exists substantial evidence, based on the analysis of individual data, that general education (schooling) increases wages. Card (1999) for instance, summarizes various Mincer-inspired studies and concludes that the impact of a year of schooling on wages is about 10%. Similar results exist for Belgium (de la Croix & Vandenberghe, 2004) and many other member countries of the Organization for Economic Co-Operation and Development (OECD). These results generally interpreted as a validation of Becker's human capital theory where more educated individuals are more productive (and thus better paid, assuming market remunerate production factors according to their marginal productivity). The puzzling element of that approach is that labour productivity is never measured or estimated. It is inferred from variation of wages/remunerations under the assumption that wage differences must reflect productivity differences.

Some macroeconomists, analysing country-level time series, also support the idea that the continuous expansion of education has contributed positively to revenue per head (Krueger & Lindahl, 2001), or production per worker (Mankiw et al, 1992). But at that level, identification of the proper contribution of education is complicated by the difficulty to separate - using cross-country data over long time periods - the causal effect of education of income, from the wealth-driven surge of the demand for education, in particular of access to tertiary education.

This chapter is based on few key considerations. First, jointly investigating the relationship between productivity, wages and workforce composition (e.g. its educational attainment) – which amounts to bridging industrial organisation and labour economics – is a promising research agenda. Second, productivity is, in essence, a firm-level phenomenon and should be primarily assessed at that level. In modern economies, where most people work inside firms, education-related productivity gains cannot possibly exist at the individual-level (as highlighted in Mincer-type analyses) if they do not show up at the firm level. Productivity is probably intrinsically determined by the (heterogeneous) ability of firms to successfully aggregate individual productivities, in conjunction with other factors of production (capital…). A similar reasoning applies to countries: the benefits of human capital should show clearly in the performance of firms, if they are to emerge at a more aggregate level. We thus argue that a study of the relationship between education, productivity and remuneration requires analysing data at the level of the firm. Individual workers' productivity is hardly ever observed. By contrast, many datasets now contain good-quality information about what firms are able to produce (e.g. firm value added). Similarly, the alignment of productivity and pay at the individual level is hard to assess. But it can be evaluated with firm-level aggregates, conditional on adoption of an adequate analytical framework, as we will show in Section 2. Workers' characteristics (e.g. their educational attainment) can be aggregated at the firm level and introduced into firm-level equations in order to explore how they influence productivity and pay/remuneration.

Surprisingly, most economists with an interest in human capital have neglected the level of the firm to study the education-productivity-pay nexus. Other characteristics of the workforce, like gender or age have, by comparison, been much more investigated at the level of the firm by industrial or labour economists (Hellerstein et al., 1999, Aubert & Crépon, 2003; Hellerstein & Neumark, 2007; Vandenberghe, 2011a,b, Vandenberghe, 2012; Rigo, Vandenberghe & Waltenberg, 2012; Dostie, 2011; van Ours & Stoeldraijer, 2011).

At present, the small literature based on firm-level evidence provides some suggestive evidence of the link between education, productivity and pay at the level of firms. Examples are Hægeland & Klette (1999); Haltiwanger et al. (1999). Other notable papers examining a similar question are Galindo-Rueda & Haskel (2005), Prskawetz et al. (2007) and Turcotte & Rennison (2004). The general consensus in this strand of research is that more educated workers are also more productive. They further conclude that there is an alignment of marginal benefit (productivity) and marginal cost (wage).

But, despite offering plausible and intuitive results, many of the above studies essentially rely on cross-sectional evidence and most of them do not tackle the two crucial aspects of the endogeneity problem affecting the estimation of production and wage functions (Griliches & Mairesse, 1995): i) heterogeneity bias (unobserved time-invariant determinants of firms' productivity that may be correlated to the workforce structure) and ii) simultaneity bias (endogeneity in input choice, in the short-run, that includes the workforce mix of the firm). While we know that labour productivity is highly heterogeneous across firms (Syverson, 2011), only Haltiwanger et al. (1999) control for firm level-unobservables using firm-fixed effects. The problem of simultaneity has also generally been overlooked. Certain short-term productivity shocks affecting the choice of labour inputs, can be anticipated by the firms and influence their employment decision and thus the workforce mix. Yet these shocks and the resulting decisions by firms' manager are unobservable by the econometrician. Hægeland & Klette (1999) try to solve this problem by proxying productivity shocks with intermediate goods, but their methodology inspired by Levinsohn & Petrin (2003) suffers from serious identification issues due to collinearity between labour and intermediate goods (Ackerberg, Caves & Frazer, 2006) (Box 2).

Our aim here is to provide a methodologically solid investigation into the connection between a key measure of firm performance: labour productivity (i.e. value added per worker) and the composition of firms' workforce in terms of educational attainment, with a particular focus on tertiary education. The latter choice echoes the, now rather dominant, view that in advanced economies like Belgium, productivity gains are driven by the expansion of tertiary education. We exploit longitudinal firm-level Belgian data (edited by Bel-first). The latest release of this data set contains longitudinal information for a sizeable sample of 9,970 firms located in Belgium for the period 2002-2011, on key outcomes and costs of the businesses, as well as the educational attainment of their workers.

Our main results indicate that the marginal productivity of workers with a university degree is significantly larger than that of workers with primary education attainment or less. In particular, our preferred specifications controlling for endogeneity and firm heterogeneity (S-GMM, FE-ACF) shows that a worker with a university degree is 23% (FE-ACF) to 42% (S-GMM) more productive than a worker with a primary education attainment or less. Workers with a 2-year college degree or only secondary school appear to be 3.4% (FE-ACF) to 18.5% more productive as primary school graduates. Simultaneously, the labour cost premium associated to workers university degree is 17.3% (FE-ACF) to 43.8% (S-GMM), and 5% (FE-ACF) to 12.4% (S-GMM) % for those with a 2-year college degree. Workers with only secondary school appear to be not more productive/expensive than workers with a primary school attainment. Hence, we interpret our results as supportive of the alignment of labour costs on productivity, and thus a validation of the Mincerian assumption.

The rest of the chapter is organized as follows. Section d.1 is devoted to an exposition of the dataset. Section d.2 contains the econometric results and Section d.3 our main conclusions.

2. Data description

We are in possession of a large unbalanced panel of around 73,794 firm-year observations corresponding to the situation of about 9,970 firms, from all sectors forming the Belgian private economy, in the period 2002 – 2011. These firms are largely documented in terms of sector (SIC), size, capital used, labour cost levels and productivity (value added). These observations come from the Bel-first database, that most for-profit firms located in Belgium must feed to comply with the legal prescriptions. All the firms occur at least 4 times in the panel; the maximum being 10 times. This seems to be a reasonable time span as most economists would a priori consider that a proper assessment of how education/human capital affects productivity requires a medium-term perspective, meaning that firms' performance need to be observed over a certain number of years for human capital's beneficial contribution to production to become visible.

Descriptive statistics, forming this large sample are reported in Table d1. Of prime interest in this chatper is the breakdown by educational attainment. Table d2 shows that, during the observed period (2002 – 2011), about 73% of the workforce of private for-profit firms located in Belgium have still, at most, an upper secondary school degree. Workers with a 2-year college degree represented 19% of the total workforce. Slightly less than 8% consisted of individuals with a (4-year) university degree. This means a mere 27% of workers with a tertiary education background;

clearly less than the percentage among the current generation of school leavers. This discrepancy logically reflects the lower propensity of older generations to stay on beyond secondary education, and complete a tertiary education programme.

Labour costs used in this chapter, which were measured independently of value added, include the value of all monetary compensations paid to the total labour force (both full- and part-time, permanent and temporary), including social security contributions paid by the employers, throughout the year. In the upper part of Table d1, one also sees that labour costs (overall labour costs per hour) is logically inferior to productivity (value-added per hour).

Figure 6.1 displays how the (log of) productivity per hour (value added per hour) evolves with the share of university- and 2-year college-educated workers for the period 2002 – 2011. These stylised facts suggest that, in the Belgian private economy, the productivity regularly rises with human capital, in particular between the 5% and the 20% range. Productivity seems to plateau for the share of 2-year college workers above the 40% threshold. At this stage any deductions can hardly be regarded as conclusive.

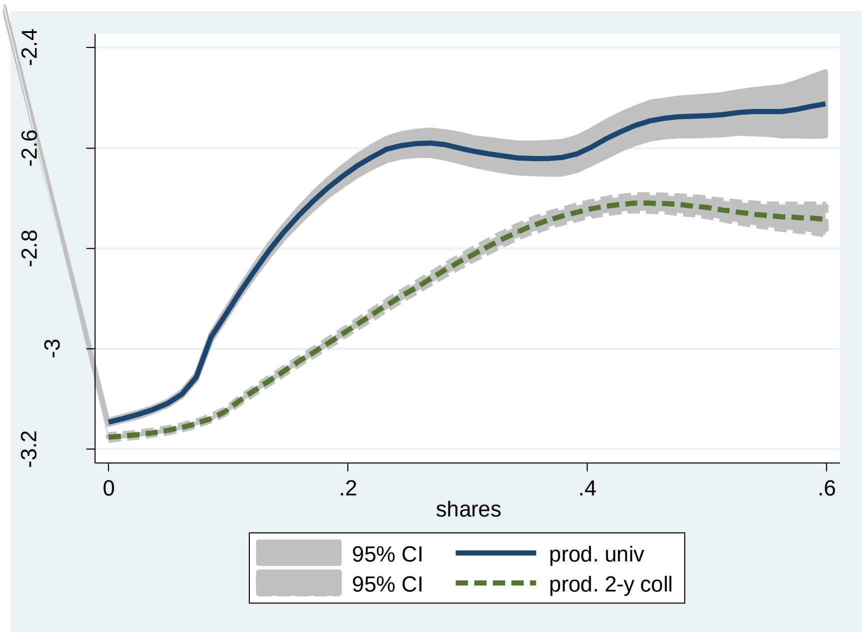
Figures 6.2 and 6.3 are essentially stylized facts that do not control for the important difference in the way workers with different educational background distribute across sectors that may dramatically differ in terms of productivity and labour cost for reasons that are independent from the educational structure of their workforces. Only adequate econometric analysis, with sector and firm fixed effects and other controls will allow us to draw more substantiated conclusions.

Table 6.1: Belfirst. Basic descriptive statistics (unbalanced panel 2002-2011)

Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Value added per hour (log)	73,794	-3.011	0.603	-10.315	4.150
Labour cost per hour (log)	73,794	-3.467	0.375	-17.476	4.052
Number of workers (log)	73,794	3.751	1.148	0.693	10.287
Number of workers	73,794	113	481	1	29,344
Capital (th. €) (log)	73,794	7.841	1.814	0	17.437
Share of workers with at most a primary education attainment	73,794	0.152	0.276	0	1
Share of workers with at most a secondary education attainment	73,794	0.582	0.341	0	1
Share of workers with a 2-year college attainment	73,794	0.188	0.231	0	1
Share of workers with a university attainment	73,794	0.078	0.156	0	1
Share of women	73,794	0.285	0.241	0	1
Number of hours worked annually per employee (log)	73,794	7.369	0.132	6.215	8.510
Share of workers with open-ended contracts	73,794	0.963	0.096	0	1

Source: Bel-first panel, our calculus

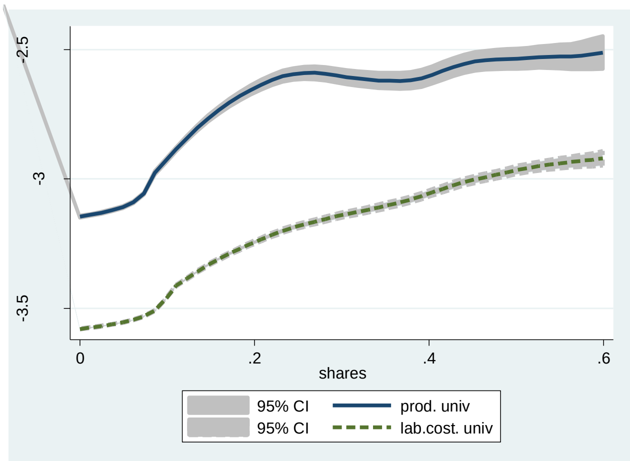
Figure 6.1: Productivity per hour according to share of University or 2-year College-educated workers. Panel 2002-2011 [95% confidence intervals]



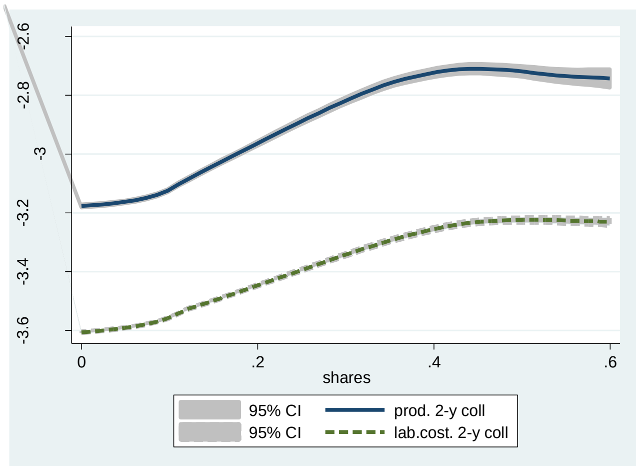
Curves on display correspond to a local polynomial smooth of *y* (i.e. log of average productivity,) on *x* (i.e. share of university- or 2-year-college-educated workers). A kernel function of the Epanechnikov type is used to calculate the weighted local polynomial estimate.

Figure 6.2: Productivity per hour and labour cost per hour. Panel 2002-2011 [95% confidence intervals]

[A] Share of university-educated workers



[B] Share of 2-year college educated workers



Curves on display correspond to a local polynomial smooth of y (i.e. log of productivity per worker or log of labour cost per workers) on x (i.e. share of university- or 2-year-college-educated workers). A kernel function of the Epanechnikov type is used to calculate the weighted local polynomial estimate.

Remember that all our regressions contain a vector of control Fit with year/sector interaction dummies. Additionally, Fit contains the share of women to control for gender based productivity differences. Our list of controls comprises also the share of workers with an open-ended contract (vs. those with a temporary contract). These are individuals who may possess more firm-specific human capital, acquired via on-the-job learning, and have developed a degree of attachment to their employer that could positively affect productivity.

Another possibility to better understand the data is to examine the evolution of the educational mix of the workforce over the observed period of time (2002 to 2011). Note that firms in our sample have experienced a marked rise of their share of better-educated workers (Table d2). On average, their share of 2-year-college-educated workers has climbed from 17.9% to 19.2%; their share of university-educated employees from 7.4 to 8%.

Intermediate inputs play a key role in our analysis, as they are central to one of our strategies to overcome the simultaneity/ endogeneity bias (Box 2). Our measure is a direct one. It is the value (in th. EUR per full-time-equivalent worker) of raw materials, consumables and other goods and services consumed or used up as inputs in production by firms.

Finally, it is clear from Table d2 that there has been a rise in the number of firms included in the panel between 2002 and 2008. This reflects the history of Bel-first's way of collecting data on educational attainment. Until 2007, reporting that information was optional and most of the (voluntary) respondents where large firms. After 2008, it became mandatory for all firms to communicate the information about the educational attainment of their workforce. The results specific to large-firms present in the panel from 2002 to 2011 are not shown here because they yield little additional insights. Qualitatively, they do not differ, but are available from the authors upon request.

3. Econometric results

Table d3 summarises the main econometric results. We first estimate the productivity and labour-cost regression with ordinary least square (OLS) (columns (1) and (2)). To account for firm unobserved heterogeneity we then turn to models with firm fixed effects (columns (3) and (4)). To account for simultaneity bias, we then turn to the structural approach proposed by ACF (columns (5) and (6)) (see Box 2). Next are our preferred models, i.e. those presenting the enviable characteristic of dealing with heterogeneity and simultaneity, in an integrated way. Columns (7) and (8) display those delivered by the model that combines FD and the ACF intermediate-goods proxy idea. The last two columns (9) and (10) present results of the system-GMM estimation. All our regressions include year*sector fixed effects. The vector of controls Fit comprises the share of women and the share of workers with an open-ended contract. The coefficients in the table should be interpreted with respect to the reference group (ie. workers/employees with at most primary education). Notice that we cannot test the hypothesis that relative marginal productivity equals relative marginal cost, because we estimate separately the regressions.

Table 6.2: Belfirst. Unbalanced panel sample of 9970 firms followed between 2002 and 2011. Basic descriptive statistics: mean

Year	Number of observations	Value added per hour (log)	Labour cost per hour (log)	Number of workers (log)	Number of workers	Capital (th. €) (log)	Share of workers with a 2-year college attainment	Share of workers with a university attainment	Share of women	Share of workers with open-ended contracts	Number of hours worked annually per employee (log)
2002	5166	-3.139	-3.593	3.906	129	7.788	0.179	0.074	0.270	0.970	7.392
2003	5439	-3.095	-3.564	3.877	121	7.833	0.182	0.076	0.273	0.969	7.389
2004	5676	-3.052	-3.533	3.861	123	7.870	0.184	0.078	0.277	0.969	7.400
2005	5832	-3.013	-3.508	3.864	126	7.958	0.191	0.0805	0.277	0.970	7.389
2006	5979	-2.970	-3.470	3.884	127	8.041	0.193	0.084	0.283	0.967	7.371
2007	6316	-2.934	-3.443	3.869	128	8.111	0.198	0.085	0.289	0.965	7.373
2008	9867	-3.019	-3.467	3.648	104	7.693	0. 175	0.069	0.287	0.959	7.370
2009	9767	-3.014	-3.421	3.651	101	7.758	0.189	0.079	0.288	0.961	7.344
2010	9957	-2.979	-3.414	3.644	103	7.797	0.192	0.081	0.290	0.959	7.352
2011	9795	-2.971	-3.397	3.627	101	7.767	0.192	0.080	0.294	0.956	7.355

Table 6.3 – Econometric results. Parameter of the production/labour cost function (std-errors). Implied relative marginal productivity/labour cost. Panel 2002-2011

	OLS		**Fixed Effect (FE)**		**ACF**		**FE-ACF**		**System-GMM à-la Blundell Bond (S-**	
	(1) Productivity per hour (log)	**(2)** Labour cost per hour (log)	**(3)** Productivity per hour (log)	**(4)** Labour cost per hour (log)	**(5)** Productivity per hour (log)	**(6)** Labour cost per hour (log)	**(7)** Productivity per hour (log)	**(8)** Labour cost per hour (log)	**(9)** Productivity per hour (log)	**(10)** Labour cost per hour (log)
$\mu_1;\mu^{w}_1$ [Secondary school]	0.016	0.043***	0.011	0.006	-0.013	0.015	0.013	0.032*	-0.003	.000
	(0.012)	(0.008)	(0.012)	(0.007)	(0.019)	(0.010)	(0.015)	(0.018)	(0.012)	(.012)
$\mu_1;\mu^{w}_1$ [2-year College]	0.230***	0.305***	0.063***	0.076***	0.139***	0.246***	0.027	0.050	0.153***	0.034**
	(0.020)	(0.013)	(0.018)	(0.011)	(0.030)	(0.015)	(0.025)	(0.031)	(0.015)	(0.014)
$\mu_3;\mu^{w}_3$ [University]	0.446***	0.765***	0.160***	0.177***	0.601***	0.664***	0.184**	0.173**	0.349***	0.356***
	(0.038)	(0.023)	(0.039)	(0.021)	(0.087)	(0.042)	(0.076)	(0.077)	(0.021)	(0.019)
Firm fixed effects	NO	NO	YES	YES	NO	NO	YES	YES	NO	NO
Controls[a]	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year*Sector fixed effects[b]	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Number of observations	73794	73794	73794	73794	73794	73794	73794	73794	73794	73794
Number of firms	9970	9970	9970	9970	9970	9970	9970	9970	9970	9970
Rsquare	0.236	0.166	0.213	0.067	-	-	-	-		
Implied relative marginal productivity/labour cost (a) [ref= Primary or less]										
$\lambda_{i1,0};\lambda^{w}_{i1,0}$ [Secondary school]	1.019	1.043	1.014	1.006	0.983	1.015	1.017	1.031*	0.996	1.000
$\lambda_{i2,0};\lambda^{w}_{i2,0}$ [2-y. college]	1.271***	1.305***	1.075***	1.076***	1.169***	1.246***	1.034	1.050	1.185***	1.034**
$\lambda_{i3,0};\lambda^{w}_{i3,0}$ [University]	1.526***	1.765***	1.193***	1.178***	1.734***	1.663***	1.234**	1.173**	1.422***	1.356***

(a) Controls: share of women and share of workers with an open-ended contract.

(b) SIC1 (#9 sectors)

*** p<0.01, ** p<0.05, * p<0.1

The basic OLS regression puts forward the presence of a relative increase in productivity of attending a 2-year college and university education with respect to primary education. Marginal productivity of a 2-year college worker is estimated to be 1.27 times larger than of workers with a primary education attainment. That of a worker with a university degree appears to be 1.52 times that of the reference group. OLS-estimated marginal labour cost convey the idea that 2-year college workers cost 1.30 times more to their employer than the reference group, whereas the corresponding ratio for university-educated workers is 1.76. Results for secondary education are not statistically significant. At this stage, we also test for the possibility that the error terms in the productivity and labour cost equations are correlated and a source of bias. We do so by estimating a seemingly unrelated regression (SUR) system. Results are not shown here but are available from the authors upon request. They are very similar the OLS results reported above.

Turning to the results of the FE model, we immediately see at the bottom of column (3) that a higher educational attainment translates into lower (marginal) productivity advantages compared with OLS. This stems from controlling for firm unobserved heterogeneity (i.e. FE), and it suggests that better-educated individuals, in particular those with a university background, concentrate in firms that are intrinsically more productive. Holding a secondary degree still does not seem to make any statistically significant difference compared with possessing a primary degree. Those with 2-year college now appear only 1.075 times more productive than the reference group (vs. 1.27 with OLS). And workers possessing university degree appear only 1.193 times more productive (vs. 1.53 with OLS). Similar falls are observed among our estimates of (marginal) labour costs. Workers with a 2-year college attainment are 1.076 times more expensive to employ than the reference group, and university graduates are 1.178 times more expensive. Note that these estimates of the relative cost of employing workers with a tertiary education attainment are almost perfectly aligned on estimates of their productivity.

OLS also potentially suffers from endogeneity bias. This justifies considering ACF i.e. using intermediate goods to proxy for a plant's unobservable short-term productivity shocks. ACF has the advantage over the more typical FE panel data approach of allowing for time-varying firm effects and allowing for more identifying variation in the other inputs. It is not, however, a complete panacea. We have explained in Section 2 that it is difficult to believe in the existence of a one-to-one relationship between a firm's consumption of intermediates goods and a term ωit that would systematically comprise all the firms' unobservables (shocks + fixed effects). ACF results (columns (5) and (6) in Table d.3 somehow comfort us in our a priori scepticism. ACF fails to take us significantly away from OLS, as point estimates are of similar magnitude.

Remember also that ACF – due to the inclusion of interaction terms between the various labour share variables is a way to allow for imperfect substitutability across labour groups and between labour and capital (Hellerstein & al., 1999). We interpret the similarity between our ACF results and those of the OLS-estimated production function as a possible indication that the assumption of perfect substitutability may not be abusive or a major source of distortion of our key estimates.

We now turn to our preferred models. We first combine ACF with firm fixed effects (FE-ACF). Results (columns (7) and (8)) show that the relative marginal productivity for secondary and 2-year college do not reach statistical significance. By contrast, university graduates still display a significant productivity advantage of 1.23 (23% more) with respect to primary school graduates. Note that FE and FE-ACF-results i) are fairly similar but ii) are much lower than those delivered by ACF which themselves tend to be similar to OLS results. This tentatively suggest that i) the simultaneity bias is not pronounced in the case of Belgian firms but ii) that firm unobserved heterogeneity is important and hint at the existence of assortative matching between workers and firms. High-productivity workplaces attract better-educated individuals, in line with the skill segregation assumption put forth by Kremer (1993) or Sattinger (1993).

Our second preferred model is S-GMM. Estimates, for both relative productivity and labour cost, are somewhat larger than those delivered by FE-ACF. A worker with a university degree appears 1.42 times (42%) more productive than workers with a primary school attainment (vs. 23% with FE-ACF). This could be explained by the fact that S-GMM does not completely evacuate data in level. This said, S-GMM results largely comfort the evidence gathered: more educated workers, in particular university graduates, are more productive than the reference category (at most primary school graduates).

Focusing on estimates of (relative) marginal contribution of education to labour cost, we come to a similar conclusion. The estimated contribution of educated workers to labour cost is positive among the different specifications. In our first preferred specification (ACF-FE) we do not find statistical significance for secondary or 2-year college, but we estimate a marginal labour cost of 1.17 times that of the reference group increase for university graduates (1.23 times in terms of productivity). With our other preferred specification (S-GMM), the corresponding estimate is 1.43 (1.42 in terms of productivity). Broadly speaking, the comparison of productivity and labour cost estimates delivered by our preferred models suggests an overall alignment.

4. Conclusions

In this chapter, we use firm-level micro data to try to validate the fact that the abundantly-documented relationship between education and wages is causally driven by a positive relationship between education and firm-level productivity. The existing empirical literature contains surprisingly little evidence of a causal relationship supporting this standard assumption of the human capital theory. The small literature that exploits on firm-level evidence provides some suggestive evidence of the link between education, productivity and pay at the level of firms. But, despite offering plausible and intuitive results, it essentially relies on cross-sectional evidence and most of it does not tackle two crucial aspects of the endogeneity of production and wage functions: heterogeneity and simultaneity. We have tried to fill that void using good-quality Belgian data, covering the private economy during the 2000s, analysed with state-of-the-art panel models that control for heterogeneity and simultaneity. Our results are essentially fourfold.

First, marginal productivity of workers with a tertiary education is positively associated with firm-level overall labour productivity. Referring to our preferred models that control for firm-level unobserved heterogeneity and simultaneity bias (FE-ACF, S-GMM), a worker with a university degree appears 23% (FE-ACF) to 42% (S-GMM) more productive than workers with a primary school attainment or less. Using Psacharopoulos' (1981) 'shortcut' method to estimating rate of return, and assuming that university graduates have studied during 10 additional years compared with the reference group (workers with at most a primary degree), these figures correspond to rates of return of 2.3 to 4.2% per year of schooling; somewhat below the 5.2% obtained by de la Croix & Vandenberghe (2004) when estimating a Mincerian gross montly wage equation.

For those with a 2-year college degree similar estimates range from 3.4% (FE-ACF) to 18.5% (S-GMM). Those for individuals with secondary school attainment are not statistically different from zero. Simultaneously, the labour cost premium of workers with university degree ranges from 17% (FE-ACF) to 43% (S-GMM) . For those with a 2-year college, it ranges from 5% (FE-ACF) to 12.4% (S-GMM). It is not significant for workers with a secondary education attainment. We interpret these results as supportive of labour costs' alignment on marginal productivity. In short, the traditional relationship between individual wages and education, highlighted in innumerable estimations of Mincerian equations, could be driven by a positive link between education and the capacity of firms to be more productive. Belgium is generally considered as a country where labour issues - in particular those related to wages and labour cost formation - are highly regulated and determined by centralised tripartite bargaining. Yet, this chapter provides evidence that, at the level of the firm, productivity remains a key determinant of pay. The alignment of marginal labour cost on marginal productive that we observe is compatible with the textbook assumption of spot labour markets.

Second, our regressions with firm-fixed effects (FE) estimates of human capital-related productivity gains are smaller in magnitude than those emerging from regressions without firm FE, but still statistically significant contrary to those obtained by Haltiwanger et al. (1999) who analysed productivity changes within US firms between 1985 and 1996. We interpret this as an indication that the gradual rise of the educational attainment of the workforce, in particular the rise of the number of university graduates, is good for the productivity of Belgian firms. At the same time, cross-sectional evidence stemming from OLS regressions is conducive to systematic exaggeration of human-capital-related productivity gains. This is because better-educated individuals self-select in, or are selected by, those of the Belgian private firms that are intrinsically more productive; something a priori in line with Kremer's assumption of skill segregation at the level of the firm (Kremer, 1993).

Third, when we account for firm-heterogeneity and simultaneity bias with the ACF methodology, we obtain similar results to those delivered by standard model with FE. We conjecture that, in our setting, the simultaneity bias is not large.

Fourth, in terms of labour demand, estimates delivered by our preferred models (FE-ACF, S-GMM) are supportive of the alignment of marginal productivity on marginal labour cost. This tentatively suggests that private firms located in Belgium face no financial incentives to modify the educational mix of their workforce.

CHAPTER 7 - The impact of training on productivity and wages

1. Introduction

The accumulation of human capital plays an important role in explaining economic performance and long-term growth (Lucas 1988). Mostly the focus lies on skill acquisition through the general education system. However, on-the-job training plays a crucial role as well because it can not only maintain, but also improve human capital of the workforce.

While there exists a vast literature estimating the returns to training, which focused mainly on the impact on wages, there are only a few papers that also analyzed the impact of training on productivity. Moreover, the focus in these papers is either on the impact on wages or on the productivity premium of training. In contrast, this paper analyzes the impact of on-the-job training on both wages and productivity, which matters for understanding the economic mechanisms behind training. The theoretical foundations of on-the-job training have originally been formalized by Becker (1964) who made a distinction between general and specific training. Under perfect competition, firms will not pay for general training of their workers as they can leave the firm searching for better paid work, which compensates them for the increased productivity acquired through general training. Hence, the worker is the sole recipient of general training benefits and will also bear the costs of it. Yet, in a series of papers Acemoglu and Pischke (1998, 1999a, 1999b) argue that a substantial amount of training is paid for by firms and is still general in nature. They show that a necessary condition for firms to pay for general training is a compressed wage structure, caused by imperfections in the labor market such as monopsony. With a compressed wage structure, training increases the marginal product of labor more than the wage, which creates incentives for the firm to invest in general training.

This chapter contributes to the literature along various dimensions. First, we make use of a large firm level longitudinal data set which contains information on measures of training, such as the proportion of workers that received training, the number of hours they were trained and the cost of training. This data allows us to measure the impact of training on both wages and productivity at the firm level. By focusing on firm level data we are able to avoid possible aggregation biases and hence capture the effects of training more precisely. Second, the analysis at the firm level and the panel structure of the data allows us to control for the endogeneity of training. To this end, we estimate production functions applying recent econometric techniques, in particular, control function approaches, taking into account training decisions and hence we control for the endogeneity of training. In addition, the production function estimates provide us with a measure of unobserved worker ability which we include in the wage equation to retrieve a consistent estimate for the impact of training on wages as in Frazer (2001). Third, our data allows us to explore how the impact of training on wages and productivity is affected by worker heterogeneity related to the type of worker contracts, human capital and gender.

We find that an increase in the share of trained workers by 10 percentage points is associated with 1.7 percent to 3.2 percent higher productivity, depending on the specification. However, consistent with the theoretical insights about wage compression and training, this increase in productivity is not entirely offset by a similar increase in wages. The average wage per worker only increases by 1.0 to 1.7 percent in response to the same increase in training.

2. Data

Data is obtained from the Belfirst database. This database, commercialized by Bureau Van Dijck, includes the income statements of all Belgian incorporated firms. We obtained an unbalanced panel for the period 1997-2006 of both manufacturing and non-manufacturing firms with at least one worker. We select a number of key variables needed for estimation of the production function and wage equation such as value added, number of employees (in full time equivalents), labor costs, material costs and the capital stock. In addition, Belgian firms are required to report information about formal training they provide to their employees. In particular, they have to report the number of employees that followed some kind of formal training as well as the hours spent on this training and the training costs. This allows us to obtain a firm-level measure of training for more than 135,000 Belgian firms active in manufacturing and non-manufacturing sectors. However, only a fraction of these firms have to report material costs, which we will need in our empirical strategy.

Table 1 provides some summary statistics of the full dataset as well as of the restricted sample of firms reporting material costs. A Belgian firm active in the private sector employs on average 21.6 employees, generates around 1.3 million euros value added per year and has an average labor cost of around 35,400 euro. Manufacturing firms are on average larger compared to non-manufacturing firms. The average proportion of trained workers is equal to 3.2%, mainly due to the low number of firms providing training to their employees. In firms that train their workers in a given period, around 50% of the employees benefit from this training which lasts approximately one work week, namely 39.1 hours and costs 1, 414 € to the firm. The training duration and costs are somewhat larger in the manufacturing sector compared to the non-manufacturing sector.

We report as well the summary statistics for the subsample of firms reporting material costs. The subsample consists of typically larger firms which are more likely to provide training to their employees. The costs and duration of training however, are approximately the same as in the full sample.

3. Results

Using various specifications and estimation methods, our results indicate that the productivity increase associated with training is larger than the wage increase. More precisely, effective labor input increases by 1.7% to 3.2% in response to an increase of 10 percentage points in the fraction of workers that receive training while the average wage increases by only 1% to 1.7%. This difference between the productivity premium and the wage premium is statistically significant and robust across a wide range of specifications. Furthermore, we find a slightly higher impact of training in non-manufacturing compared to manufacturing sectors. Our results are robust also across different specifications and definitions of the training variable (hours of training versus fraction of workers following training). And we also take into account various measurement issues, estimation methods and sources of worker heterogeneity (blue collar versus white collar).

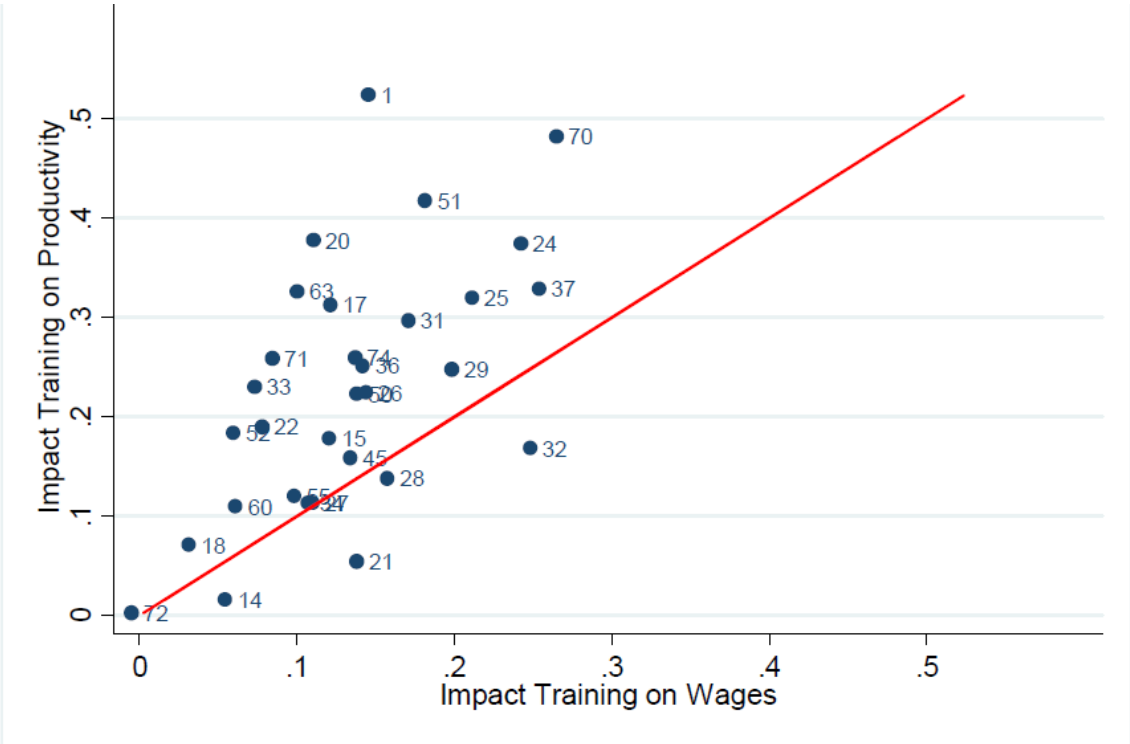
Table 7.1 Summary statistics

	Total	Manufacturing	Non-Manufacturing
Full Sample			
Value Added (×1000€)	1,319	3,216	973
Capital Stock (×1000€)	1,043	1,985	872
Employment	21.6	40.9	18.1
Labor Costs per Worker (×1000€)	35.4	35.0	35.5
Observations	804,293	109,196	695,097
Nr. Firms	135,865	14,160	121,705
Proportion of Trained Workers	.032	.061	.026
Proportion Trained Workers in Training Firm	.503	.455	.526
Cost of Training per Worker Trained (€)	1,414	1,508	1,368
Hours Training per Worker Trained	39.1	43.1	37.2
Restricted Sample			
Value Added (×1000€)	8,288	12,727	6,343
Capital Stock (×1000€)	6,482	7,679	5,957
Employment	105.0	150.9	84.9
Labor Costs per Worker (×1000€)	47.4	43.6	48.9
Observations	91,045	27,738	63,307
Nr. Firms	15,495	4,131	11,364
Proportion of Trained Workers	.167	.222	.142
Proportion Trained Workers in Training Firm	.486	.466	.500
Cost of Training per Worker Trained (€)	1,516	1,561	1,482
Hours Training per Worker Trained	36.7	40.9	33.7

All figures refer to the unweighted average of each variable. The restricted sample refers to firms reporting material costs.

Our results seem to hold across a broad range of sectors, although there is quite some heterogeneity across sectors in terms of the productivity and wage premium. Figure 1 combines the estimates for the wage and productivity premia for various sectors (NACE rev1.1). The 45-line is plotted, such that all observations above this line represent sectors for which the impact of training on productivity is larger than the impact of training on wages. Most of the sectors are located above this line which is consistent with Acemoglu and Pischke (1998, 1999a,b). The correlation between the productivity and wage premium equals 0.64 and is highly significant. Acemoglu and Pischke (1998, 1999a,b) show that firms will pay for general training when the internal wage structure is compressed, meaning that the wage function increases less steeply in general skills than the marginal product. Wage compression can be caused by a variety of labor market frictions, such as search costs and informational asymmetries leading to monopsony power. Ideally, we would like to relate our sector level estimates for the wedge between the productivity and wage premium of trained workers to a measure for monopsony power at the sector level. A positive correlation would support the view that our finding of a positive wedge between the wage and productivity premium can be best explained by a combination of general training and a compressed wage structure.

Figure 7.1 Impact training on productivity and wages



We also provide initial evidence that the majority of training is general in nature and hence our results are consistent with recent theories such as Acemoglu and Pischke (1998,1999a,b) which explain firm provided general training by imperfect competition in the labor market and wage compression. This finding can have important policy implications. The standard result of Becker (1964) is that if workers are not credit constrained, training investments are efficient and government intervention is unnecessary or should be directed to the credit markets. However, with imperfect labor markets and a compressed wage structure, there could be underinvestment in training from a social point of view. For example, when making their training decisions, firms do not take into account the possible externalities for future employers of trained workers (Acemoglu and Pischke 1998, 1999a,b). This opens possibilities for the government to implement training subsidies.

CHAPTER 8 - Educational mismatch and firm productivity

1. Introduction

Educational mismatch (or simply over- and under-education) refers to the difference between the worker's attained level of education and the education required in the job. This important phenomenon, first highlighted by Freeman (1976), has been extensively studied, especially since the late 1980s, in order to evaluate the consequences of the continued expansion of participation rates in higher education that are observed in developed economies (McGuinness, 2006). For many decades, advanced economies have implemented policies aiming to increase the level of education of their labour force. The 'European strategic framework on education and training', for instance, aims to raise the share of people aged between 30 and 34 with tertiary education to 40 percent on average in the European Union by 2020. This strategy implicitly assumes that there is excess demand for tertiary education or that firms employing more educated workers will improve their production techniques to take advantage of those additional skills (McGuinness, 2006). However, if these assumptions are not satisfied then workers with tertiary education may end up in jobs for which they are over-educated. Moreover, in periods of excess labour supply, there may be some 'crowding out', i.e. a process by which workers with tertiary education take up jobs that could be occupied by less educated ones.

The proportion of over-educated workers in the OECD area stands today at around 25 percent and about 1 out of 5 workers is recorded as under-educated (OECD, 2011). Given the magnitude of these figures, "many observers point to: i) the failure of the education system in providing youth with the skills required at work, and ii) the inability of labour markets to sort many workers to suitable jobs" (OECD, 2011, p. 193). Moreover, McGuinness (2006) emphasizes that educational mismatch may be costly for the economy as a whole (e.g. a waste in tax revenues due to the financing of excessive levels of education), for firms (e.g. a loss in efficiency if over-educated workers are less productive than their adequately educated colleagues) but also for individuals (e.g. over-educated workers may earn less than their former classmates doing jobs that match their education).

What do we know from existing research? The incidence and earnings effects of educational mismatch are well documented in the economic literature and findings are quite consistent (Hartog, 2000, Leuven and Oosterbeek, 2011). They notably show that, in a given job with a specific level of required education, over- (under-) educated workers earn more (less) than those who have just the required education for the job (Battu et al., 1999, Dolton and Vignoles, 2000, Frenette, 2004, McGuinness, 2003, van der Meer, 2006). In contrast, the evidence regarding the impact of over- and under-education on firm productivity is mixed, indirect and subject to various potential biases. A first strand of the literature relies on human capital theory to infer the consequences of educational mismatch on productivity. As a result, productivity effects of over- and under-education are deduced from the latter's impact on wages. Other studies examine how educational mismatch influences job satisfaction and other correlates of workers' productivity (such as absenteeism, shirking, turnover or training).

The "human capital" and "job satisfaction" approaches lead to quite different conclusions. While the former suggests that over- (under-) educated workers are more (less) productive than their adequately educated colleagues in similar jobs, the latter provides ambiguous predictions. Both approaches also suffer from important methodological limitations. Indeed, the relationship between education, wages and productivity is likely to be much more complex than that put forward by standard human capital theory. In addition, empirical results suggest that the correlation between job satisfaction and job performance reaches at most 30 percent (Judge et al., 2001). It may thus be quite misleading to focus solely on job satisfaction to estimate the productivity effects of educational mismatch. Finally, over-education probably affects productivity through other channels than job satisfaction (and correlated workers' attitudes and behaviours). For instance, in line with human capital theory, it could be argued that the (possible) negative effect on firm productivity of over-educated workers through their (potential) lower degree of job satisfaction could (at least partially) be compensated by their additional skills and capabilities acquired in school.

Given the inconclusiveness and shortcomings of the existing literature, there is an obvious need for further research. To paraphrase Hartog (2000), it would be highly informative if we knew the effect of over- and under-education on productivity, rather than on wages, job satisfaction and related workers' attitudes and behaviours (such as absenteeism, shirking, turnover or training). This is the purpose of the present paper. We rely on an ORU (Over-, Required and Under-education) specification that has been aggregated at the level of the firm, we use the average firm-level value added per worker as dependent variable and we apply the dynamic system GMM estimator to representative linked employer-employee panel data for Belgium covering the years 1999-2006. We thus examine how mean years of over- and under-education within firms affect the productivity of the latter, conditional on mean years of required education. Moreover, as the relationship between educational mismatch and productivity is likely to be more pronounced for recent labour market entrants (Verhaest and Omey, 2009), we also add to the literature by investigating whether the effects of educational mismatch on firm productivity vary according to the age of over- and under-educated workers. Finally, the richness of our data allows us to control for important econometric issues that are often neglected in other studies, such as the potential endogeneity of educational mismatch, the existence of firm unobserved fixed effects, cohort effects and the state dependence of firm productivity.

The remainder of this chapter is organized as follows. A review of the literature is presented in the next section. Sections 3 describes our methodology. The impact of educational mismatch on firm productivity is analysed in section 4. The last section discusses the results and concludes.

2. Background

Two types of approaches have been considered in the literature to examine the impact of educational mismatch on productivity in a microeconomic framework. The first one relies on standard human capital theory (Becker, 1964). According to this theory, i) education (as well as formal training and informal work experience) develops skills that make workers more productive and ii) wage differentials reflect differences in productivity. Consequently, the impact of over- and under-education on productivity might be inferred from the latter's effect on wages. This strategy has been followed for instance by Rumberger (1987). His results, based on U.S. cross-sectional data for the late 1960s and 1970s, show that the wage differential for a year of over-education is positive but lower than that for a year of required education. Therefore, he suggests that: "additional schooling is not completely unproductive, but simply that jobs constrain the ability of workers to fully utilize the skills and capabilities they acquire in school" (Rumberger, 1987, p. 46). Other studies regarding the wage effects of educational mismatch also highlight that, in a given job with a specific level of required education, over- (under-) educated workers earn more (less) than those who have just the required education for the job (Battu et al., 1999, Dolton and Vignoles, 2000, Duncan and Hoffman, 1981, Groot, 1996, Groot and Maassen van den Brink, 2000, Sicherman, 1991, van der Meer, 2006). Although part of this premium (penalty) may be explained by workers' unobserved heterogeneity (Bauer, 2002, Chevalier, 2003, Dolton and Silles, 2008, Frenette, 2004, Lamo and Messina, 2010, McGuinness, 2003, McGuinness and Sloane, 2011), current evidence on the basis of human capital theory thus suggests that over- (under-) education increases (reduces) workers' productivity.

Another strand of the literature examines the impact of educational mismatch on job satisfaction and other correlates of workers' productivity (such as absenteeism, shirking, turnover or training). The standard hypothesis is that over-educated workers, as a result of frustration, are less satisfied, have more health problems and higher rates of shirking, absenteeism and turnover than their adequately educated colleagues. Given that all these factors are likely to have a negative impact on productivity, the assumption is that firms are reluctant to hire over-educated applicants (Büchel, 2002). The relationship between job satisfaction and job performance has been extensively studied by industrial psychologists. Their results indicate that the satisfaction-performance correlation is positive but not strong: close to 0.30 according to the meta-analysis of Judge et al. (2001) and around 0.17 according to that of Iaffaldano and Muchinsky (1985). Under the hypothesis that over-education leads to less job satisfaction, this finding suggests that educational mismatch may hurt productivity but to a limited extent. Empirical studies investigating the impact of ORU on job satisfaction (and other correlates of workers' productivity) provide mixed results. Hersch (1991) for instance finds, with cross-sectional data collected in the Eugene (Oregon area, U.S.) in 1986, that over-educated workers (both male and female) and female under-educated workers are less satisfied than their adequately educated colleagues in similar jobs. In addition, his results show that male over-educated workers are more likely to quit their job and that over-educated workers (both male and female) benefit less from training. The study of Tsang et al. (1991), based on U.S. cross-sectional data from the late 1960's and 1970's, also supports the hypothesis that male workers who are (highly) over-educated tend to be less satisfied and more inclined to quit their job. Yet, unlike Hersch (1991), Tsang et al. (1991) report no significant effect of over-education on job satisfaction for female workers. Relying on West-German cross-sectional and longitudinal data covering the period 1984 to 1995, Büchel (2002) finds no significant relation between over-education and job satisfaction. He also shows that over-educated workers are healthier, more strongly work- and career-minded, more likely to participate in on-the-job training and to have more years of tenure with the same firm than their adequately educated colleagues in jobs with similar requirements. Using a survey of school leavers in Flanders (Belgium) that was conducted in 1999 and 2002, Verhaest and Omey (2006) support the standard hypothesis that over-educated workers have a higher turnover rate than those who have just the required education for the job. However, they find no robust results regarding the impact of over-education on job satisfaction and training participation. Moreover, their results for under-educated workers are generally unclear. In a more recent exercise, Verhaest and Omey (2009) apply a shadow price approach to study the relation between over-education and job satisfaction. Their results based on an extended version of their survey of Flemish school leavers (interviewed in 1999 and the early 2000s) show that over-educated workers are significantly less satisfied than their adequately educated colleagues in similar jobs, even after controlling for individual fixed effects. They also highlight that the wage premium earned by over-educated workers with regard to those who have just the required education for the job only partially compensates for their lower utility (i.e. satisfaction). Finally, their results indicate that the negative consequence of over-education on satisfaction diminishes with years of work experience. In contrast to the above mentioned literature, Tsang (1987) does not only investigate the effect of over-education on job satisfaction but he also constructs a firm-level job-satisfaction index and estimates the latter's impact on firm productivity using a Cobb-Douglas production function. His results, based on individual- and firm-level data from twenty-two U.S. Bell companies for the period 1981-1982, indicate that over-education is significantly and negatively related to job satisfaction, which is in turn positively and significantly related to output. They thus suggest that over-education is detrimental for firm productivity in the telephone industry.

Overall, it turns out that the two approaches developed in the literature to uncover productivity effects of educational mismatch lead to different conclusions. Earnings effects of over- (under-) education suggest on the basis of human capital theory that over- (under-) educated workers are at least slightly more (less) productive than those with the required education for the job. In contrast, studies focusing on job satisfaction (and other correlates of workers' productivity) provide inconsistent predictions from a firm's point of view. This is due to the fact that the consequences of educational mismatch on job satisfaction are still unsettled when using an ORU specification (which is obviously the most appropriate when considering the firm perspective).

Both approaches also suffer from important methodological limitations. The human capital approach is based on the hypothesis that both human capital and earnings are directly proportional to individual productivity on the job (Rumberger, 1987). However, the relationship between human capital, wages and productivity is likely to be more complex. On the one hand, human capital may only have a limited impact on productivity. Signaling theory (Spence, 1973, 1979), for instance, puts forward that a worker's productivity is a sort of intrinsic quality that does not really depend on education but rather on other factors such as family background, individual history, innate quality or talent (Cahuc and Zylberberg, 2004, Riley, 2001). While signaling theory finds some empirical support (Groot and Oosterbeek, 1994), it is however unlikely to completely discount the role of human capital (Chevalier et al., 2004). On the other hand, wages may not only reflect marginal productivity. Indeed, non-competitive models of wage determination (including collective bargaining, rent-sharing, search and recruiting frictions, discrimination or monopsony) find some support in the empirical literature (Bayard et al., 2003, Blanchflower and Bryson, 2010, du Caju et al., 2011, Manning, 2003, Martins, 2009, Mortensen, 2003, Rusinek and Rycx, 2012). Workers with identical productive characteristics thus not necessarily receive the same wages.

The second approach, focusing on job satisfaction (and other correlates of workers' productivity), is also limited methodologically. A first point is that many studies investigate the direct impact of over-education on job satisfaction but neglect potential indirect effects (Verhaest and Omey, 2009). Typically, over-educated workers are found to earn more than those who have just the required education for the job. Given that job satisfaction depends positively on workers' wages, one should control for wages and more generally for any job characteristic related to satisfaction to compute the net effect of over-education on job satisfaction. Surprisingly, this is not always the case in the literature. It is also worthwhile to recall that the impact of job satisfaction on job performance is found to be modest (Judge et al., 2001). Therefore, even if it could be shown that over-educated workers are less satisfied with their jobs, the extent to which over-education affects firm productivity would remain unclear. Finally, it should be highlighted that educational mismatch may affect productivity through other channels than job satisfaction (and correlated workers' attitudes and behaviours). Indeed, in line with human capital theory, it could be argued that even if over-educated workers are less satisfied with their jobs, they may be more productive than their adequately educated colleagues in similar jobs simply because they have more years of education. To put it differently, a lower degree of job satisfaction might be compensated by additional skills and capabilities acquired in school so that the net effect of over-education on productivity might even be positive or simply non significant.

In sum, the evidence regarding the impact of over- and under-education on productivity is mixed, indirect and subject to various shortcomings. A decade ago, Hartog (2000) already emphasized that it would be highly informative if we knew the effect of over- and under-education on productivity, rather than on wages, job satisfaction and related workers' attitudes and behaviours. Surprisingly, his statement is still valid. Therefore, in this paper we investigate the direct impact of ORU on a precise measure of firm productivity, namely the average value added per worker. We also examine whether the consequences of educational mismatch for firm productivity vary according to the age of over- and under-educated workers.

3. Methodology

Three different measures, based respectively on job analysis, worker self-assessment and realized matches, have been proposed in the literature to estimate the required education for a job and the incidence of educational mismatch. Each measure has its own advantages and weaknesses (for a discussion see e.g. Hartog, 2000). In this article, we use realized matches. So, the required education for a job is computed by taking the mode of workers' years of education within each ISCO three-digit occupation (113 categories). A worker is then defined as over- (under-) educated if his attained years of education are higher (lower) than those required in his occupation.

To examine the impact of educational mismatch on firm productivity, we use an ORU specification that has been aggregated at the level of the firm. More precisely, we estimate the following firm-level productivity equation:

$$\ln VA\_work_{j,t} = \beta_0 + \beta_1\left(\ln VA\_work_{j,t-1}\right) + \beta_2\left(\frac{1}{m_{j,t}}\sum_{i=1}^{m_{j,t}} REQ_{i,j,t}\right) + \beta_3\left(\frac{1}{m_{j,t}}\sum_{i=1}^{m_{j,t}} OVER_{i,j,t}\right)$$

$$+ \beta_4\left(\frac{1}{m_{j,t}}\sum_{i=1}^{m_{j,t}} UNDER_{i,j,t}\right) + X_{j,t}\beta_5 + Z_{j,t}\beta_6 + \gamma_t + \upsilon_{j,t} \quad (1)$$

with :

VA_workj,t the productivity of firm j at year t, measured by the average value added per worker.

mj,t the number of workers employed in firm j at year t.

REQi,j,t the required years of education for the job of worker i in firm j at year t, i.e. the mode of years of education in worker's i occupation at the ISCO 3-digit level (across the entire economy) at time t.

OVERi,j,t = (Attained_educationi,j,t – REQi,j,t) if > 0, 0 otherwise.

UNDERi,j,t = (Attained_educationi,j,t – REQi,j,t) if < 0, 0 otherwise.

Attained_educationi,j,t the number of years corresponding to the highest level of education attained by worker i employed in firm j at time t.

Xj,t is a vector containing aggregated characteristics of workers, namely the share of the workforce that has at least 10 years of tenure, the fraction of workers respectively younger than 25 and older than 49 years, and the share of women, blue-collar and part-time workers.

Zj,t includes firm characteristics, namely the sectoral affiliation (8 dummies), age and size (number of workers) of the firm, conditional dispersion in hourly wages and level of wage bargaining (1 dummy).

$\gamma_{j,t}$ is a set of year dummies (7 dummies).

$\upsilon_{j,t}$ is the error term.

Equation (1) describes the relationship between average years of over-, required and under-education within firms and the productivity of the latter, when controlling for year dummies and mean worker and firm characteristics. The inclusion of the lagged dependent variable among the regressors accounts for the potential state dependence of firm productivity and aims to improve the identification of the parameters of interest in our preferred specification, i.e. system GMM (see discussion below). Equation (1) has been estimated with three different methods. The baseline regression relies on the pooled Ordinary Least Squares (OLS) estimator with standard errors robust to heteroscedasticity and serial correlation. This estimator is based on both the cross-section variability between firms and the longitudinal variability within firms over time.

Pooled OLS estimators of value added models have been criticized for their potential "heterogeneity bias" (Aubert and Crépon, 2003, p. 116). This bias is due to the fact that firm's productivity depends to a large extent on firm-specific, time-invariant characteristics that are not measured in micro-level surveys. As a consequence, the OLS regression coefficients associated to ORU variables are likely to be biased since unobserved firm characteristics may affect simultaneously the firm's level of value added and its workforce average level of educational mismatch. This is referred to as a problem of spurious correlation and could be caused by factors such as an advantageous location, firm-specific assets like the ownership of a patent or other firm idiosyncrasies. To account for the unobserved time-invariant heterogeneity of firms, we re-estimated equation (1) with a fixed effects estimator (and standard errors that are robust to heteroscedasticity and serial correlation within firms (Huber/White/sandwich estimate of variance)). A fixed effects model does not estimate the level of productivity of firm i, but the change in productivity. Time-invariant heterogeneity is by definition not linked to changes in productivity and therefore controlled for.

An additional problem to address is the potential simultaneity between firm productivity and educational mismatch. As highlighted by Gautier et al. (2002, p. 523), "employers might exploit cyclical downturns to improve the average skill level of their work force". To put it differently, there might be some cyclical 'crowding out', namely a process by which during recessions - because of excess labour supply – highly educated workers take the jobs that could be occupied by less educated ones. This assumption, supported empirically for certain countries including Belgium (Cockx and Dejemeppe, 2002, Dolado et al., 2000, Teulings and Koopmanschap, 1989), suggests that mean years of over-education within firms may increase as a result of a lower labour productivity (and vice versa). To control for this endogeneity issue, in addition to state dependence of firm productivity and the presence of firm fixed effects, we estimate equation (1) using the dynamic system Generalized Method of Moments (GMM) estimator proposed by Arellano and Bover (1995) and Blundell and Bond (1998).

4. Data and descriptive statistics

Our empirical analysis is based on a combination of two large data sets covering the years 1999-2006. The first, carried out by Statistics Belgium, is the 'Structure of Earnings Survey' (SES). It covers all firms operating in Belgium that employ at least 10 workers and with economic activities within sections C to K of the NACE Rev. 1 nomenclature. The survey contains a wealth of information, provided by the management of firms, both on the characteristics of the latter (e.g. sector of activity, number of workers, level of collective wage bargaining) and on the individuals working there (e.g. age, education, tenure, gross earnings, paid hours, sex, occupation). The SES provides no financial information. Therefore, it has been merged with a firm-level survey, the 'Structure of Business Survey' (SBS). The SBS, also conducted by Statistics Belgium, provides information on financial variables such as firm-level value added and gross operating surplus per worker. The coverage of the SBS differs from that of the SES in that it does not cover the whole financial sector (NACE J) but only Other Financial Intermediation (NACE 652) and Activities Auxiliary to Financial Intermediation (NACE 67). The merger of the SES and SBS datasets has been carried out by Statistics Belgium using firms' social security numbers.

A first point to consider for the econometric specification is that information in the SES refers to the month of October in each year, while data in the SBS are measured over entire calendar years, that is, over all months from January to December of each year. Hence, to avoid running a regression where information on the dependent variable precedes (to a large extent) the date on which the explanatory variables have been recorded, all explanatory variables in equation (1), except the lagged dependent variable, have been lagged by one year. In this way, information on educational mismatch relative to the month of October in year t is used to explain firm-level productivity in year t+1. This methodological choice (and the use of a dynamic model) restricts our sample to firms that are observed in at least two consecutive years. Moreover, it leads to the over-representation of medium-sized and large firms given that sampling percentages of firms in our data set increase with the size of the latter (see footnote 18). Next, we exclude workers and firms for which data are missing or inaccurate. In order to guarantee that the required education is computed on a reasonable number of data points, we also eliminate occupations at the ISCO three-digit level with less than 10 observations. Finally, we drop firms with less than 10 observations, the reason for this being our use of average values at the firm level as control variables.

Our final sample consists of an unbalanced panel of 8,954 firm-year-observations from 3,062 firms. It is representative of all medium-sized and large firms in the Belgian private sector, with the exception of large parts of the financial sector (NACE J) and the electricity, gas and water supply industry (NACE E).

Table 8.1: Means and standard deviation of selected variables, 1999-2006

Variables:	**Mean**	**Std. Dev.**
Annual added value per worker (€[1])	89,788	649,572
Annual value added per worker (ln)	11.07	0.61
Required education (years)	11.77	1.35
Over-education:		
Percentage workers	22.53	23.28
Years	0.59	0.65
Under-education:		
Percentage workers	27.60	26.53
Years	-0.93	1.01
Intra-firm wage dispersion (€[1, 2]):	0.17	0.09
Workers with 10 years of tenure or more (%)	38.06	24.38
Women (%)	26.94	23.91
Share of workers < 30 years	8.10	8.74
Share of workers between 30 and 49 years	75.69	12.59
Share of workers > 49 years	16.25	12.18
Blue-collar workers[3] (%)	54.60	33.93
Part-time (less than 30 hours per week, %)	16.18	16.75
Size of the firm (number of workers)	252.57	275.04
Firm-level collective agreement (%)	30.63	45.80
Sector (%):		
Mining and quarrying (C)	0.70	
Manufacturing (D)	56.10	
Electricity, gas and water supply (E)	0.36	
Construction (F)	9.31	
Wholesale and retail trade, repair of motor vehicles, motorcycles	12.26	
Hotels and restaurants (H)	1.69	
Transport, storage and communication (I)	6.62	
Financial intermediation (J)	1.34	
Real estate, renting and business activities (K)	11.62	
Number of observations	8,954	
Number of firms	3,062	

[1] At 2006 constant prices. [2] Hourly residual wage dispersion after controlling for human capital variables and workers' characteristics in a wage equation following the Winter-Ebmer and Zweimüller (1999) methodology (i.e. standard deviations of residuals of wage regressions run for each firm and each year separately). [3] The distinction between blue- and white-collar workers is based on the International Standard Classification of Occupations (ISCO-88). Workers belonging to groups 1 to 5 are considered to be white-collar workers (1: Legislators, senior officials and managers; 2: Professionals; 3: Technicians and associate professionals; 4: Clerks; 5: Service workers and shop and market sales workers) and those from groups 7 to 9 are considered to be blue-collar workers (7: Craft and related trades workers; 8: Plant and machine operators and assemblers; 9: Elementary occupations).

Table 8.1 depicts the means and standard deviations of selected variables. It indicates that the mean number of required years of education at the firm-level is equal to 11.77. The corresponding proportion of over- and under-educated workers within firms stands respectively at around 23 and 28 percent. Put differently, the average years of over- and under-education within firms are respectively equal to 0.59 and -0.93. Moreover, we find that the average annual value added per worker is approximately equal to 89,800 EUR, around 27 percent of the workers within firms are women, 55 percent are blue collar, 76 percent are prime-age workers (i.e. between 30 and 49 years old), 38 percent have at least 10 years of tenure and 16 percent are part-timers (i.e. work less than

30 hours per week). On average, firms employ 253 workers and they are essentially concentrated in the manufacturing sector (56 per cent), wholesale and retail trade, repair of motor vehicles, motorcycles and personal and household goods (12 percent), real estate, renting and business activities (12 percent), construction (9 percent) and transport, storage and communication (7 percent).

5. Results

Benchmark specification

We first estimated equation (1) by pooled OLS with standard errors that are robust to heteroscedasticity and serial correlation. As highlighted in section 4, explanatory variables have been lagged by one year to make sure that information on productivity does not precede information on educational mismatch. Results presented in the second column of Table 8.2 show that lagged productivity has a significant and positive impact on its contemporaneous value. Moreover, we find that an additional year of (average) required education within a firm has a positive and significant effect on firm productivity. The regression coefficient associated to required years education is equal to 0.017. This coefficient suggests that when the required level of education in a firm increases by one year, the firm's productivity rises by 1.7% on average the year after. Regarding educational mismatch, we find that mean years of over-education exert a significant positive influence on firm productivity, while the reverse result is found for mean years of under-education. Indeed, results indicate that firm's productivity rises (decreases) on average by 1.6% (0.9%) following a one unit increase in mean years of over-education (under-education) the year before.

However, these results suffer from the fact that time-invariant unobserved workplace characteristics are not accounted for. Therefore, we re-estimated equation (1) with a fixed effects estimator. Results, presented in the third column of Table 8.2, show again that productivity depends significantly and positively on its lagged value. However, the corresponding elasticity drops from 0.819 to 0.152 after controlling for fixed effects. As regards the estimate for the required level of education, it decreases from 0.017 to 0.008 and becomes statistically insignificant (p-value = 0.13). Coefficients on mean years of over- and under-education also turn out to be statistically insignificant when controlling for firm-level time-invariant heterogeneity.

Table 8.2: Educational mismatch and firm productivity
(OLS, Fixed-effects and GMM estimates, 1999-2006)

Dependent variable:	***Value-added per worker (ln)***		
	(1)	**(2)**	**(3)**
Value-added per worker	0.819***	0.152***	0.553***
Required education	0.017***	0.008	0.024***
Over-education	0.016***	0.003	0.035***
Under-education [1]	0.009**	-0.001	0.012
Worker characteristics [2]:	Yes	Yes	Yes
Firm characteristics [3]:	Yes	Yes	Yes
Year dummies (7):	Yes	Yes	Yes
R-squared	0.774		
Within R-squared		0.043	
Sig. Model (p-value)	0.000	0.000	0.00
Hansen statistic			346.1
Arellano-Bond statistic (AR2) [4]			1.36
Number of observations	8,954	8,954	8,954
Number of firms	3,062	3,062	3,062

Table 8.3: Educational mismatch and firm productivity
(GMM estimates, controlling for cohort effects, 1999-2006)

Dependent variable:	***Value-added per worker (ln)***	
	(1) GMM-SYS [5]	**(2) GMM-SYS [5]**
Value-added per worker	0.553***	0.557***
Required education	0.023***	0.021***
Over-education	0.033***	
Under-education [1]	0.015	
Over-education among young workers		0.031*
Over-education *among* older workers		0.027**
Under-education among young workers [1]		0.035**
Under-education among older workers [1]		0.001
Worker characteristics [2]:	Yes	Yes
Firm characteristics [3]:	Yes	Yes
Year dummies (7):	Yes	Yes
Sig. Model (p-value)	0.000	0.000
Hansen statistic	352.4	386.1
Arellano-Bond statistic (AR2) [4]	1.32	1.35
Number of observations	8,954	8,954
Number of firms	3,062	3,062

Notes: ***/**/* significant at the 1, 5 and 10% level, respectively.

Robust standard errors are reported between brackets.

[1] By definition, mean years of under-education take negative values in our data set (see equation (1), Table 8.1). Therefore, a positive regression coefficient should be interpreted as follows: when mean years of under-education increase (decrease), i.e. become less (more) negative, productivity rises (drops).

[2] Share of the workforce that: i) has at least 10 years of tenure, and ii) is younger than 25 and older than 49 years, respectively. The share of women, blue-collar and part-time workers as well as the conditional dispersion in hourly wages are also included.

[3] Sectoral affiliation (8 dummies), number of workers, age of the firm and level of wage bargaining (1 dummy).

[4] AR2 displays the test for second-order autocorrelation in the first-differenced errors.

[5] First and second lags of explanatory variables, excluding time dummies, are used as instruments.

Yet, these estimates are still inconsistent due to the endogeneity of ORU variables. To account for this issue (but also for state dependence of productivity and firm fixed effects), we re-estimate equation (1) using the dynamic system GMM estimator proposed by Arellano and Bover (1995) and Blundell and Bond (1998). Variables in the differenced equation are thus instrumented by their lagged levels and variables in the level equation are instrumented by their lagged differences. Time dummies are considered as exogenous and we use first and second lags of other explanatory variables as instruments. Results are presented in the last column of Table 8.2. To examine their reliability, we first apply the Hansen (1982) test of overidentifying restrictions and Arellano-Bond's (1991) test for second-order autocorrelation in the first differenced errors. As shown in Table 8.2, they respectively do not reject the null hypothesis of valid instruments and of no autocorrelation. As expected, we also find that current productivity is to a significant and important extent related to its past value. Interestingly, the coefficient on the lagged dependent variable falls between the OLS and fixed effects estimates. As outlined by Roodman (2009), this result supports the appropriateness of our dynamic system GMM specification. The regression coefficient on the average required years of education within firms is now significant at the 1% level and equal to 0.024. This value suggests that when the required level of education in a firm increases by one year, the following period the firm's productivity rises on average by 2.4 percent. Results regarding the productivity effects of educational mismatch are also somewhat different from those obtained with the fixed effects estimator. As in the OLS specification, they now indicate that over-education has a significant positive influence on firms' value added. More precisely, they show that firm's productivity increases on average by 3.5% following a one unit increase in mean years of over-education. The reverse result is found for under-education. However, the coefficient on this variable (equal to 0.012) is only significant at the 11% level.

Controlling for the birth cohort of workers

Although the results reported so far take into account a range of issues related to the measurement of productivity and required education, they could nevertheless be misleading given that our indicators of ORU do not control for the birth cohort of workers. Indeed, given that years of education have substantially increased over time and that labour market experience could be a substitute to formal education, it may be more appropriate to determine whether a worker is over- or under-educated by comparing his level of education with the mode of the education among workers of a similar generation employed in the same occupation. Put differently, given that education and workers' age (i.e. a proxy for labour market experience) are probably the best variables in our data set to evaluate skills, as a robustness test it is worth computing ORU variables for workers belonging to a similar age group (i.e. with similar experience).

Practically, we considered two age groups and fixed the threshold for young and older workers at 35 years. Next, we computed the required education separately for young and older workers and defined a worker as over-educated (under-educated) if his level of education is higher (lower) than that required for workers belonging to the same age group and occupation at the ISCO 3-dgit level. Finally, equation (1) has been re-formulated such that: i) the average of the years of required education in firm j at time t equals the employment weighted sum of the required years of education for all jobs occupied respectively by young and older workers in firm j at time t, and ii) the average of the years of over-education (under-education) in firm j at time t corresponds to the sum of the years of over-education among young and older workers in firm j at time t, divided by the total number of workers employed in firm j at time t.

This new specification has been estimated with the dynamic system GMM estimator, which controls for firm fixed effects, simultaneity issues and dynamics in adjustment process of firm productivity. Results are presented in the second column of Table 8.3. To test their reliability, we applied the Hansen (1982) test of overidentifying restrictions and Arellano-Bond's (1991) test for second-order autocorrelation in the first differenced errors. As shown in Table 8.3, they support the consistency of our estimates. We also find that current productivity is to a significant and important extent related to its past value. As regards ORU variables, results again show that: i) productivity depends positively and significantly on average required years of education within firms, ii) mean years of over-education have a significant positive effect on firms' value added, and iii) mean years of under-education have a negative but insignificant effect (p-value = 0.11) on firm productivity[1]. Also noteworthy is that the magnitude of the regression coefficients associated to the ORU variables are not very different from those obtained on the basis of equation (1). Overall, it thus appears that our conclusions regarding the impact of ORU variables on firm productivity remain unchanged after controlling for the birth cohort of workers.

Results according to workers' age

A complementary issue that deserves to be investigated is whether the effects of educational mismatch on firm productivity vary according to the age of over- and under-educated workers.

From a theoretical point of view, we may expect the relationship between educational mismatch and productivity to be more pronounced for younger workers given that our indicators of over- and under-education are more likely to represent a real mismatch in skills for new labour market entrants. Indeed, one could argue that older workers can more easily compensate their lack of formal schooling (that is their 'under-education') by additional work experience and training. Moreover, workers who do not possess the required education for their job and who are no able to catch up (through training and work experience) will probably have (or choose) to exercise a less demanding job (in the same company or elsewhere) as they get older. On the other hand, skills learned at school tend to depreciate and to become obsolete over time so that older workers are less likely to have skills in excess of those required for their job. A related point is that workers whose 'over-education' is really beneficial for firm productivity are more likely to get promoted and to exercise a job matching their skills as they grow older. Overall, these arguments suggest that older over- and under-educated workers are less likely to affect productivity than their younger counterparts.

However, these predictions may not be verified. Indeed, older under-educated workers could still exert a negative impact on firm productivity if labour market experience is an imperfect substitute to formal education and that undereducated workers who are not able to catch up remain in their jobs. On the other hand, it is possible that over-educated workers have a higher level of competence all over their career. Over-educated workers could for instance persistently: i) be more creative and independent, ii) adapt easier to a changing environment, iii) learn new skills faster and iv) have more ability to perform complex tasks and to interact with colleagues than workers having just the required education for the job. As a result, the positive effect of over-education on firm productivity may not vanish as over-educated workers get older.

To test the impact of educational mismatch on productivity for young and older generations of workers, as shown in the online appendix, we included as explanatory variables in our benchmark equation (that does control for cohort effects) mean years of over- and under-education respectively

[1] See footnote 24.

among young and older workers in each firm. Results obtained with the dynamic system GMM estimator are presented in the third column of Table 8.3. Statistical tests do not reject the null hypothesis of valid instruments and of no autocorrelation. Moreover, we find that lagged productivity has a significant positive impact on its current value. As regards ORU variables, results first show that when the required level of education in a firm increases by one year, the firm's productivity rises on average by 2.1% the year after. Secondly, they indicate that mean years of over-education – both among young and older workers – have a significant positive influence on the firm's value added. More precisely, firm's productivity is found to rise on average by respectively 3.1 and 2.7% following a one unit increase in mean years of over-education among young and older workers the year before. Finally, findings show that mean years of under-education among young workers are detrimental for firm productivity. Indeed, an increase of one year in the incidence of under-education among young workers is found to decrease productivity on average by 3.5% one year later. By contrast, results reveal that years of under-education among older workers have no significant productivity effects.

Standard t-statistics indicate that the effect on productivity is not statistically different for an additional year of required and over-education (both among young and older workers). Combining this result with the stylized fact that over-educated workers earn ceteris paribus less (more) than those who have the same attained education (than those who are doing the same job) but are correctly matched (McGuinness, 2006), one might expect that firms hiring proportionally more over-educated workers will be more profitable. To examine this issue, we re-estimated our benchmark equation (controlling for cohort effects) with the dynamic system GMM estimator using as dependent variable firm profitability, i.e. the gross operating surplus per worker. This variable is equal to the difference between the firm's value added at factor costs and personnel expenses (including employee social security contributions) divided by the total number of workers employed in the firm. Results, presented in Appendix 2, show that lagged profitability has a significant positive impact on its current value. In contrast, over-, required and under-education variables are not found to have any significant effect on firm profitability (even when over- and under-education variables are split according to workers' age). Although caution is required due to possible measurement errors in profits, results do not seem to support the hypothesis that firm's profitability depends positively on mean years of over-education. Findings rather suggest that the positive impact of over-education on productivity is neutralized by a comparable upward effect on wages, so that in the end profits remain unchanged. Moreover, results appear compatible with the idea that the negative impact of young under-educated workers on firm productivity is counterbalanced by a wage penalty for those workers so that profits are unaffected.

6. The effect of overeducation in different work environments

In this section we summarize EDIPO research that provides first evidence regarding the direct impact of educational mismatch on firm productivity across working environments. More precisely, we explored the way working environments, differentiated by (i) the level of skills required by the job, (ii) the degree of technological/knowledge intensity, and (iii) the uncertainty of the economic context, may influence the relation between educational mismatch variables and productivity.

We found that a higher level of required education impacts significantly and positively firm productivity but also that increasing the level of over- (under-)education fosters (hampers) firm productivity. These results can be easily reconciled with the literature on the wage effects of educational mismatch. Indeed, they support the assumption that over- (under-)educated workers earn more (less) than those who have just the required education for the job because they are more (less) productive than the latter. On the contrary, our results are not in line with the hypothesis that over-educated workers are less productive because of frustration and a lower degree of job satisfaction.

As regards the role of working environments, we started by considering the skills required by the job. Our results suggest that over-education exerts a positive and significant impact on productivity whatever the type of skills required by firms. Yet, the impact of over-education is found to be significantly stronger among firms with a larger fraction of high-skilled jobs. Put differently, results suggest that over-educated workers contribute more to firm value added when the latter require higher on the job skills. These findings seem compatible with Brown's (1990) assumption according to which worker's productivity is more "workers' quality" sensitive when jobs require higher skills. At the same time, they also appear to back up the idea that mean workforce quality depends positively upon the share of over-educated workers within firms as the latter i) are more likely to have better unobserved characteristics (as suggested e.g., by Weiss (1995)), and ii) generate intra-firm knowledge spillovers and benefit from positive externalities from highly educated co-workers (as highlighted in e.g., in Booth and Snower (1996)). In contrast, our results do not support the hypothesis that over-educated workers would hamper firm productivity due to frustration potentially exacerbated in a less skills' demanding environment.

We then studied the influence of the firm's level of technology/knowledge on the ORU-productivity nexus, by distinguishing between high- and low-technology/knowledge firms according to a nomenclature developed by Eurostat. Our results support the assumption of a higher return for over-education in firms qualified as technology/knowledge intensive. This provides evidence that over-educated workers are even more productive in a high-tech/knowledge environment, and supports the notion of adaptability developed by Nelson and Phelps (1966), according to whom over-educated workers should benefit from a high-tech/knowledge context. The results also support the idea, suggested by Krueger and Kumar (2004), of a higher level of productivity among over-educated, who would benefit from a moving technological environment due to their higher capability to react.

Finally we investigated whether a different response from productivity to educational mismatch appears according to the uncertainty of the economic context. Our results suggest a higher return for over-education in firms that are operating in more uncertain contexts, which tends to confirm the role of over-educated workers in these situations, as developed by Bulmahn and Kräkel (2002), thanks to the improvised and ad hoc solutions they can bring to the firm. They also confirm the predominance of the adaptability criterion developed by Stankiewics (2004), according to which over-educated workers are more flexible, more adaptable, and thus more productive in uncertainty.

As regards the moderating role of working environments in the effects of under-education on productivity, conclusions are somewhat less clear-cut as results vary across specifications. Yet, a more uncertain economic context is systematically found to accentuate the detrimental effect of under-education on productivity.

It is finally worth mentioning that the three working environments assessed can be related to some extent, as jobs requiring higher skills, high-tech/knowledge firms, and firms that operate in a more uncertain context all correspond to challenging and changing working conditions. A similar trend can thus theoretically be expected, and our empirical results indeed suggest that over-educated workers would be more productive in firms that (i) require higher skills, (ii) rely on high-technological/knowledge processes for their production, and (iii) operate in a more uncertain economic context.

7. Discussion and conclusion

This chapter is a first attempt at measuring the direct impact of educational mismatch on firm productivity. It also adds to previous research by examining whether the consequences of educational mismatch on firm productivity vary according to the age of over- and under-educated workers. From a methodological point of view, we relied on an ORU (Over-, Required and Under-education) specification that has been aggregated at the level of the firm; we used as dependent variable the average firm-level value added per worker and we applied the dynamic system GMM estimator to representative linked employer-employee panel data for Belgium covering the years 1999-2006. We thus examined how mean years of over- and under-education (among young and older workers) within firms affect the productivity of the latter, conditional on mean years of required education.

Controlling for simultaneity issues, time-invariant unobserved workplace characteristics, cohort effects and dynamics in the adjustment process of productivity, we find that: i) a higher level of required education exerts a significantly positive influence on firm productivity, ii) additional years of over-education (both among young and older workers) are beneficial for firm productivity, and iii) additional years of under-education (among young workers) are detrimental for firm productivity.

These results suggest that: i) over-educated workers are more productive all over their career due to additional skills and capabilities acquired through schooling, and ii) under-educated workers either succeed to compensate their lack of productivity by additional work experience and training or end up in less demanding jobs as they get older. Our results can also easily be reconciled with the literature on the wage effects of educational mismatch. Indeed, they tend to support the hypothesis that over-educated (young under-educated) workers earn more (less) than those who have just the required education for the job because they are more (less) productive than the latter. On the contrary, our results do not support the hypothesis that over-educated workers are less productive because of frustration and a lower degree of job satisfaction. We may not exclude that, for a given job, educational mismatch may lead to less job satisfaction and worse correlated workers' attitudes and behaviours. However, it appears that the net effect of over-education on productivity is significant and positive. This finding is not surprising given that: i) estimates of the satisfaction-performance correlation reach at most 30 percent (e.g. Judge et al., 2001), ii) the literature regarding the impact of ORU on job satisfaction provides mixed results (e.g. Büchel, 2002, Hersch, 1991, Tsang et al., 1991, Verhaest and Omey, 2006), and iii) educational mismatch is likely to affect productivity through other channels than job satisfaction (and correlated workers' attitudes and behaviours), e.g. following human capital or assignment theories (Becker, 1964, Sattinger, 1993), it could be argued that a lower degree of job satisfaction might be compensated by additional skills and capabilities acquired in school so that the net effect of over-education on productivity might be positive (as suggested by our results).

A better understanding of the influence of workers' fixed unobserved characteristics on productivity is an important question for future research. It would also be interesting to test the stability of our results using: i) ORU variables that are computed on the basis of job analysis or worker self-assessment approaches, or ii) panel data covering a larger number of years. Yet, at the moment these robustness tests cannot be performed for the Belgian economy given data limitations.

PART IV – At-risk group: immigrants

CHAPTER 9 - Measurement of wage Discrimination against foreigners

1. Introduction

Immigration flows into OECD countries are marked by both sharp fluctuations and considerable diversity between countries. Taken all countries together, however, net immigration has been consistently positive since the 1960s. The first decade of the new century witnessed a new surge of inflows: between early 2000 and late 2010, the stock of foreign-born residents in the OECD rose by around 35% from 75 millions to 100 million (OECD 2014: 1). In 2011, foreign-born individuals represented less than 10% in most Eastern European countries, Greece and Portugal; between 10% and 20% in the rest of the European Union and the US; and more than 20% in Australia, Canada, Luxembourg and Switzerland (OECD 2014). Also the employment rate of immigrants differs across countries: in 2012, it has been lower compared to the native-born population in the European Union (with the exception of the Czech Republic, Hungary, Italy, Poland, Portugal and Slovakia) and higher in Luxembourg and the US (OECD 2014).

In this chapter we are concerned with the relationship between the employment of foreigners and wages, a field of intense empirical and theoretical research in labour economics since the 1950s (Becker 1957, Chiswick 1978, Arrow 1998, Altonji et Blank 1999, Cahuc et Zylberberg 2004, Salama 2010). Common to much of the empirical research in this area is the observation that foreign workers with comparable productivity-related characteristics than natives receive on average lower wages (Bevelander and Veenman 2008, Chiswick et al. 2008, Aeberhardt et al. 2010). The relevance of this relationship partly stems from its connection to a series of distributional issues, and especially concerns about discrimination and retributive justice. It is also related to other policy debates on immigration, for instance whether countries with wage penalties fail to attract skilled foreign labour or whether the labour supply increase due to immigration exerts downward pressure on native wages.

Wages of foreigners have been studied at different scales, with cities, regions and countries being the most popular levels of analysis (Borjas and Katz 2007; Dustmann et al. 2013; Mitaritonna et al. 2014). While studying wage discrimination at these levels is often justified on empirical and theoretical grounds (Ottaviano and Peri 2012), they are unable to capture appropriately the most important explanans in economic wage theory: labour productivity. Arguing that the latter depends to a large extent on the immediate context in which the employee operates – how much capital is at her disposition? how qualified are her co-workers? what type of technology does the firm use? etc – a small strand of the literature started to explore wage discrimination against foreigners with firm-level data (Hellerstein et al. 1999; Aydemir and Skuterud 2008).

The chapter is structured as follows. Section 2 presents our methodological approach for measuring the relationship between foreign employment, on the one hand, and average and relative wages at the firm level on the other hand. Section 3 presents our dataset and descriptives, whereas Section 4 includes the results of our regression analysis that are discussed in the concluding Section 5.

2. Measurement methods

Relaxing the assumption of constant wage gaps

In addition to the measurement methods presented in Chapter 2, in this chapter we build on a new solution developed by Bartolucci (2014) that a) avoids the specification of the functional form of the productivity equation but nevertheless directly uses firm-level productivity data to measure discrimination against foreigners; b) neither assumes perfect competition in the labor market nor a linear relationship wages and productivity (it allows for non-unitary wage-productivity elasticities); and c) produces a measure of wage discrimination against foreigners that is robust to labor market segregation. The wage-setting equation proposed by Bartolucci is similar to the wage equation in the Hellerstein-Neumark framework but directly estimates a parameter for the logarithm of average firm-level productivity. Assuming a standard Cobb-Douglas production function with quality-adjusted labour and perfect substitutability between worker groups, the integration of measured productivity yields the following wage equation:

$$\log\left(\overline{w}_{j,t}\right)=\alpha_j+\beta\log(\overline{p}_{j,t})+\gamma I_{j,t}+\lambda X_{j,t}+\varepsilon_{j,t} \qquad (1)$$

where the dependent variable log($\overline{w}$ j,t) is the logarithm of the average hourly wage in firm j in year t; the variable log($\overline{p}$j,t) the logarithm of average hourly productivity; Ijt is the proportion of immigrants and γ the parameter that captures wage discrimination; Xjt is a vector containing a set of observable characteristics of firm j and its labour force in year t. In addition to Equation 1, we estimate a second equation that distinguishes between the proportions of male immigrants, female immigrants and female natives (respectively denoted as IMjt, IWjt and NWjt –male natives are the reference category):

$$\log\left(\overline{w}_{j,t}\right)=\alpha_j+\beta\log(\overline{p}_{j,t})+\gamma_{IM}IM_{j,t}+\gamma_{IW}IW_{j,t}+\gamma_{NW}NW_{j,t}+\lambda X_{j,t}+\varepsilon_{j,t} \qquad (2)$$

An issue that has so far not received any attention is that the interpretation of the Hellerstein-Neumark wage equation relies on the implicit assumption of constant wage gaps. This can be illustrated with a simple numerical example of a firm with three employees, two natives and one foreigner. Imagine that estimating a firm-level wage equation similar to Equation 1 tells us that an increase in the share of foreigners of 17 percentage points, which corresponds to adding a second foreigner to the firm in our example, is correlated with a decrease in the average hourly wage from 16 to 15.5 euros. This effect could occur if the ceteris paribus wage of the two natives in our firm equals 17 euros while both the initial and the additional immigrant earn only 14 euros; in this case, the wage gap between native and foreign workers is constant and equals 3 euros before and after hiring the second immigrant.

However, the average firm wage is always sensitive to two distinct effects: changes in the shares and in the respective remuneration of natives and foreigners. In our numerical example, the lower average wage of 15.5 euros could just as well be the result of a decrease in the native wage from 17 to 16 euros combined with an increase in the immigrant wage from 14 to 15 euros; in this case, the wage gap would have narrowed from 3 to 1 euro. It is striking that none of the existing applications of the Hellerstein-Neumark method, including Bartolucci (2014), discusses the implications of changes in the wage gap.

How worried should we be about dynamic relationships between labour force composition and wage gaps? First of all, it should be noted that many policy debates consider these dynamics as the most important criterion for assessing the economic impacts of ethnic or cultural mixity. The influential report on immigration for the UK House of Lords, for instance, argues that the focus of the economic impact assessment of immigration “should be on the effects of immigration on income per head of the resident population” (Select Committee 2008: 5). Evidence in Carrington and Troske (1998a) suggests that increases in the share of black workers in US manufacturing firms is associated with decreases in the wages of black workers and increases in the wages of their white colleagues. Borjas and Katz (2007) have estimated that Mexican immigration in the US has adversely affected the earnings of less-educated native workers but improved the earnings of college graduates. The House of Lords report summarizes available evidence from the UK as suggesting that immigration has had only a small negative (positive) impact on the lowest-paid (higher-paid) workers in the UK, but also that it had stronger adverse earnings effects for “a significant proportion of previous immigrants and workers from ethnic minority groups” (Select Committee 2008 : 28). Aslund and Skans (2010) find that both immigrants and natives earn less when the share of immigrant coworkers is greater in Swedish firms, whereas Dustmann et al. (2011) conclude that the share of immigrants is positively related to the wages of immigrants in Germany. Conversely, results in Böheim et al. (2012: 17) suggest that firm-level ethnic worker heterogeneity affects wages positively but also find “a strong negative impact of a worker's own group size on wages”. Mitaritonna et al. (2014) find a positive relationship between immigration and the wages of natives, which is consistent with evidence in Ottaviano and Peri (2012) that the wage gap between immigrants and natives increases in the proportion of immigrants. While the literature on the magnitude and sign of the wage gap dynamics is therefore still inconclusive, this brief overview suggests that the interpretation of Hellerstein-Neumark or Bartolucci wage coefficients could be off the mark if we ignore that wage differentials are actually a moving target.

In this paper, we address this issue empirically and complement the estimation of Equation 1 with insights from a regression in which we replace the dependent variable with the observed gap between the average hourly wage of natives ($\overline{w}$N,j,t) and immigrants ($\overline{w}$I,j,t) in firm j at time t:

$$(\overline{w}_{N,j,t} - \overline{w}_{I,j,t}) = \alpha*_{j} + \beta*\log(\overline{p}_{j,t}) + \gamma* \ I_{j,t} + \lambda*X_{j,t} + \varepsilon*_{j,t} \qquad (3)$$

While the parameter γ in Equation 1 allows comparing our results to Bartolucci’s (2014) estimates of wage discrimination without IV, Equation 3 provides complementary insights as to the potential dynamics of the native-immigrant wage gap that are captured by parameter γ*: while significantly negative values of γ indicate wage discrimination against immigrants, the paramater γ* directly captures whether the share of immigrants is related to wider or narrower native-foreigner wage gaps.

3. Data and descriptive statistics

Data set

Our empirical analysis is based on a combination of two large data sets spanning the period 1999-2010. The first is the Structure of Earnings Survey (SES). It covers all firms operating in Belgium that employ at least 10 workers and with economic activities within sections C to K of the NACE nomenclature (Rev. 1). The SES provides no financial information. Therefore, it has been merged with a firm-level survey, the Structure of Business Survey (SBS). Our final sample consists of an unbalanced panel of 9,430 firms and 555,963 individuals, yielding 23,712 firm-year-observations during the 12 year period (1999-2010). It is representative of all medium-sized and large firms employing at least 10 employees within sections C to K of the NACE Rev. 1 nomenclature, with the exception of large parts of the financial sector (NACE J) and almost the entire electricity, gas, and water supply industry (NACE E).

Definition of main variables

Our earnings measure corresponds to total gross wages, including premia for overtime, weekend or night work, performance bonuses, commissions, and other premia. Work hours represent total effective remunerated hours in the reference period (including paid overtime hours). The firm's added value per hour is measured at factor costs and based on the total number of hours effectively worked by the firm's employees. All variables in the SES-SBS are provided by the firm's management and therefore more precise compared to self-reported employee or household surveys.

The OECD statistics on immigration we cited in the introduction define immigrants as individuals who reside in a different country than the one in which they were born. For at least three reasons this is an imperfect indicator for the presence of foreigners on the labour market. First, some of the "otherness" of foreign-born workers is erased through the process of assimilation: an individual who was born abroad but who spent her entire adult life in the host country is often so assimilated that she ceases to be a "foreigner" in the eyes of her employer, co-workers and even herself. Second, the children of foreign-born immigrants are by this definition not counted as "foreigners" even though they are often perceived as such in their host society. Third, while all foreigners differ to some extent from natives – even if only by the country of birth in their passport – some foreigners differ more from natives than others: a German in Austria or a Frenchman in Belgium arguably stands less out than a Turkish or a Moroccan.

In the literature on wage discrimination against foreigners, most studies operationalize the distinction between foreigners and natives by using information on the country of birth and/or the nationality of the individual. For instance, Böheim et al. (2012: 15) distinguish between Austrian-born workers and those born in any other country. The authors use country of birth rather than nationality on the grounds that "ethnic background may be more relevant for productivity spillovers than citizenship". As argued above, the simple native-foreigner dichotomy is problematic because it does not account for the unequal otherness of foreigners: for instance, it does not distinguish between the different socio-economic status of German and Turkish immigrants in Austria. Another problem with this definition is that "being a foreigner" can be associated with both the country of birth and the nationality of an individual.

For the case of Belgium, existing evidence suggests that we can address the problem of heterogeneity among foreigners by distinguishing between individuals from the European Union and those from outside of the EU. Martens et al. (2005) show that workers born in Morocco and Turkey are underrepresented in high-wage jobs, whereas those from Western or Northern Europe are not. Similarly, a recent study by the Institute for the Equality of Women and Men (2012) finds that the distinction between EU and non-EU workers is highly relevant for explaining wage differences in Belgium. Moreover, using the criterion of EU membership has the advantage of higher policy relevance than the simple native-foreigner dichotomy since immigration policy in EU Member States cannot regulate the flow of workers with EU nationality due to the EU Directive on the right to move and reside freely. A consequence of this Directive is that Member States can only influence non-EU flows, for instance via quotas, visa, asylum policies etc.

In this chapter, we present results based on two mutually exclusive groups that define foreigners as a combination of both nationality and country of birth. The first group – "EU workers" – consists of individuals who where born in a Member State of the European Union and with a EU nationality. This is the case for 91.8% of individuals in our sample. In this group, individuals born in Belgium represent the largest share (93.9%), followed by France (1.7%), Italy (1.5%), Germany (0.8%) and the Netherlands (0.7%). The second group – "non-EU workers" – consists of individuals who where either born outside of the EU or with a non-EU nationality, which is the case for 8.2% of observations. The most frequent country of birth in this group is Morocco (21.3%), Belgium (20.9% of non-EU workers were born in Belgium but with a non-EU nationality), Turkey (12.6%), Congo (7.7%) and Serbia (4.1%).

Male and female non-EU workers represent respectively 6.4% and 1.8% of the sample (35,690 and 9,999 observations). This equals a gender ratio of 22% among non-EU workers and 27% among EU workers. It should be noted that the relatively small share of women in the sample is not a bias but merely reflects the fact that women are underrepresented in the Belgian private-sector economy on which we focus in this paper.

Individual-level statistics

Table 9.1 shows descriptive statistics for EU and non-EU employees over the period 1999-2010. In order to examine gender differences within these two groups, we show separate means for men and women. The average hourly wage is the highest for EU men (16.3 euros) and lowest for non-EU women (13.4 euros). On average, EU women and non-EU men earn roughly the same (around 14.25 euros). The average wage for the entire sample is 15.6 euros and the average wage gap between foreigners and natives 11%; the foreigner-native gap is 14.8% among men and 6.7% among women. However, these averages mask the distribution of wages within each group. The density plots in Figure 1 show that the distribution of non-EU men and women (black curves) is more compressed compared to EU workers (grey curves). Moreover, the density curves of both EU and non-EU women (solid lines) peak at lower hourly wages compared to the curves of both male groups (dashed lines), but the curve for EU women (in grey) lies above the curve for non-EU men (in black) for wages above 16 euros.

Figure 9.1: Distribution of hourly wages by immigrant status and gender

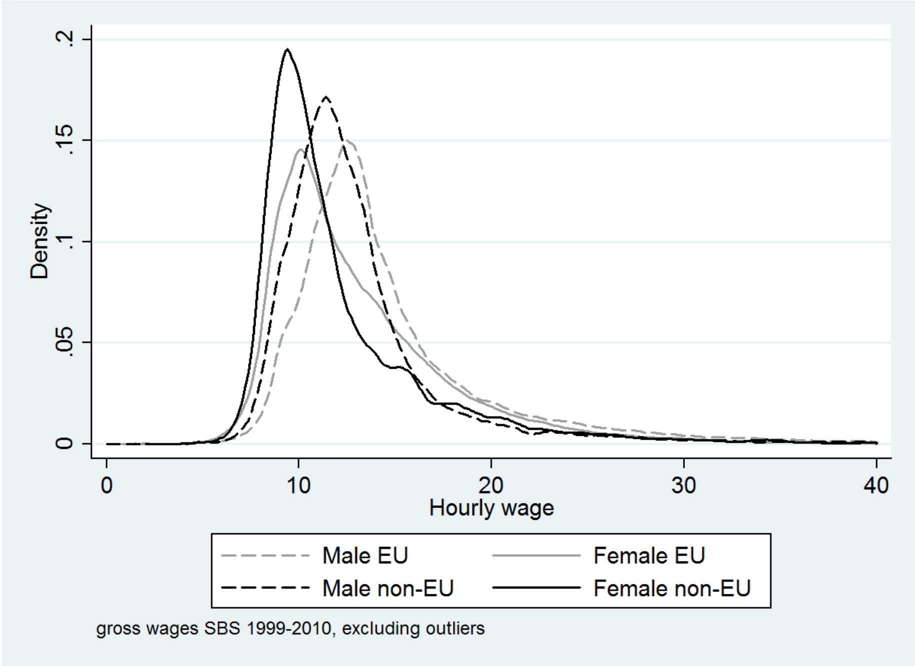


Figure 9.2: Distribution of immigrant shares by gender.

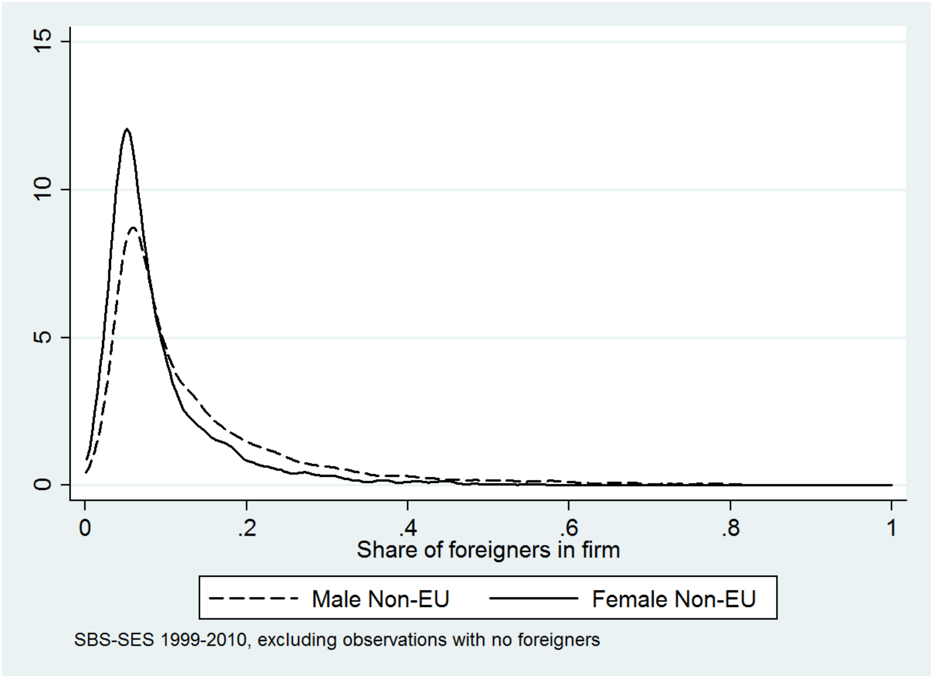


Table 9.1 underlines why it is important to take differences in human capital and sorting into jobs, sectors and regions into account. Indeed, the four groups under analysis have distinct statistical profiles. Women in our sample are on average better educated than men, although the difference between non-EU women and EU men is only small. Non-EU men are by far the group with the lowest human capital from schooling. The group of foreigners is on average younger compared to natives, with EU men being the oldest and non-EU women the youngest group in the sample. The occupational distribution reflects both the gender dimension and immigrant status: both EU and non-EU men are overrepresented in crafts and among machine operators. While there are more EU men in managerial positions and among professional and technical occupations, non-EU men are relatively more frequent in service and elementary occupations. Women are overrepresented in clerical, service and elementary occupations, whereas non-EU women are more concentrated in elementary and EU women in clerical occupations. The biggest differences in the sectoral distribution of men and women are found in the predominantly male construction sector; in the overrepresentation of women in whosesale and retail trade as well as in real estate, renting and business services. Foreigners are overrepresented in the hotel and restaurant sector. Non-EU women are strongly underrepresented in manufacturing. Whereas foreign men work on average for relatively small firms (measured in terms of the size of the workforce), foreign women work in larger firms. Finally, Table 9.1 shows the relative concentration of foreigners in the Brussels region and their marked underrepresentation in Flanders.

A simple way to explore these descriptives is to apply the conventional method for disentangling the productivity effects and wage discrimination by regressing human capital and compositional characteristics on the logarithm of individual hourly wages. In our sample, an OLS Mincer equation yields a coefficient of determination of 54% and a negative and significant coefficient for the non-EU dummy equal to -0.04, thus suggesting that a non-EU worker whose observed characteristics are identical to a EU worker suffers from a wage penalty of 4%. This is in line with results from an Oaxaca-Blinder decomposition which indicates that around 77% of the gross wage gap in our sample can be attributed to observable differences. The highest contribution to the explained part in the Oaxaca-Blinder decomposition comes from individual and job characteristics (60.1% of the explained wage gap), while firm characteristics also matter (31%). Introducing interaction variables between immigrant status and gender improves the fit of the OLS Mincer equation: the coefficient of determination rises by 3 percentage points and all three interaction variable are highly significant. Compared to the reference group of EU men, the ceteris paribus wage penalty of non-EU men remains at around 4%. Women appear to suffer from relatively higher discrimination because the respective coefficients for non-EU and EU women are -0.15 and -0.14 (all three interaction coefficients are significantly different from each other). As explained above, however, these results suffer from severe methodological issues and need to be complemented with more sophisticated identification techniques.

Table 9.1. Sample means by immigrant status and gender (1999-2010).

Variable	Individual level Male	Female	Male	Female	Total	Firm level Total
Wage/hour (constant euros)	16.3	14.3	14.2	13.4	15.6	15.3
St. deviation	(8.57)	(8.08)	(7.94)	(7.83)	(8.45)	(5.47)
Worker characteristics						
Education level 1 (ISCED 1-2)	35.7	26.7	50.7	35.8	34.5	34.0
Education level 2 (ISCED 3-4)	41.9	42.1	34.8	36.7	43.4	42.2
Education level 3 (ISCED 5-7)	22.4	31.2	14.4	27.5	24.2	23.8
Workers < 40 years	52.4	58.9	63.0	69.8	55.0	54.7
Occupations						
Managers	4.3	2.4	2.1	1.8	3.7	3.8
Professionals	10.1	9.2	6.7	10.1	9.7	9.2
Technical ass. Professionals	8.0	7.7	4.8	6.1	7.7	7.4
Clerical occupations	11.1	38.2	6.3	25.5	17.7	18.1
Service occupations	4.1	10.1	5.9	13.4	5.9	6.0
Crafts	31.0	10.9	32.9	10.0	25.8	27.1
Machine operators	23.1	10.8	21.9	7.1	19.7	19.0
Elementary occupations	8.2	10.8	19.4	26.1	9.9	9.4
Firm characteristics						
Mining and quarrying	0.0	0.0	0.0	0.0	0.0	0.0
Manufacturing	48.7	40.9	44.1	24.7	46.1	46.0
Electricity, gas and water	0.0	0.00	0.0	0.0	0.0	0.0
Construction	15.2	3.1	15.6	1.9	12.0	13.2
Wholesale and retail trade	15.1	24.1	11.8	17.6	17.2	17.5
Hotels and restaurants	1.4	3.3	6.4	12.8	2.4	2.3
Transport, storage and	8.2	6.3	8.8	6.5	7.7	7.1
Financial intermediation	1.0	2.6	1.0	2.5	1.3	1.2
Real estate, renting and bus.	9.9	19.4	12.1	33.7	12.8	11.8
Firm size	83.9	89.1	74.4	90.7	80.9	64.3
Added value/h (constant euros)	55.5	57.5	53.5	62.3	56.0	56.4
Region						
Flanders	62.1	62.2	49.0	45.3	61.0	61.2
Brussels	11.6	16.2	26.8	36.4	14.2	13.2
Wallonia	26.3	21.6	24.1	18.3	24.9	25.6
Number of observations	373728	136546	35690	9999	555963	23712
Share of sample (%)	67.2	24.6	6.4	1.8	100	100

Firm-level statistics

Our identification strategy uses information on individual worker and job characteristics with matched data on their employers, including average hourly productivity in the firm. Each of the 9430 firms in our unbalanced panel is on average observed 2.5 times between 1999 and 2010.

While the composition of firms in terms of observable individual and job characteristics does not differ substantially from the individual-level descriptive statistics (see last column in Table 9.1), firm-level data allow to assess the distribution of EU and non-EU workers across firms (Aydemir and Skuterud 2008). According to Mitaritonna et al. (2014: 4), "[v]ery little attention has been devoted in the literature to the fact that a large share of firms does not hire any immigrant even in regions with very large immigrant presence". The highly unequal distribution that Mitaritonna et al. (2014) observe in France echoes findings by Böheim et al. (2012: 15) for Austria suggesting that "the employment of foreign workers is concentrated in few firms, about 50 percent of firms employ less than 15 percent of foreign workers and 10 percent of firms employ more than 50 percent of immigrant workers". In line with these studies, foreigners are found in only 53% of firm-year observations in our sample from Belgium.

The concentration of foreigners has been attributed to non-random sorting, for instance due to network effects (Aslund and Nordstöm Skans 2010). Adding the gender dimension to the analysis of non-random sorting sheds further light on the issue. In our sample, the presence of non-EU men is positively correlated with the presence of non-EU women (the corresponding significant pair-wise correlation coefficient is 0.15), whereas the share of both groups is negatively correlated to the share of EU men (the significant correlation coefficients are -0.30 between non-EU and EU men and -0.42 between non-EU women and EU men). Interestingly, the concentration effect of male and female foreigners is similar in size to the concentration of foreign and native women: the share of EU women is positively correlated with the share of non-EU women (the corresponding coefficient equals 0.16, i.e. slightly higher than the correlation between male and female foreigners).

Figure 2 shows the distribution of firms with respect to their respective shares of male and female foreigners (the plot is restricted to the firm-year observations employing any non-EU workers). We observe that both distributions are highly skewed and illustrate that the vast majority of firms have less than 20% of foreigners on their payroll; only very few firms are composed of more than 40% and virtually none of more than 80% of foreigners.

4. Estimation results

Wage-setting equations

Regression results for the Bartolucci firm-level wage-setting model are presented in Table 9.2. The first four columns show alternative specifications of a pooled OLS estimator in order to illustrate the impact of different forms of observed heterogeneity. The wage gap between EU and non-EU employees is captured by the parameter γ. In the first model without control variables, this corresponds to the gross wage differential and is estimated to be -0.24, i.e. a 10 percentage point increase in the share of foreigners is on average associated with a 2.4% decrease (= 0.1*-0.24) of the average hourly wage in Belgian firms. This effect is sharply reduced once we include observed individual and job characteristics: the same increase in the foreigner share is now associated with a 0.6% decrease in average wages, whereas a 10 percentage point rise in the share of female workers is related to a 2.3% drop in wages. Segregation of foreigners across sectors and regions accounts for around 50% of this wage penalty but affects the female wage penalty only marginally (column 3). The full-blown specification of Equation 1 includes the average hourly productivity in the firm and other firm-level control variables (firm size and capital stock) on the right-hand side (column 4). The productivity parameter β is positive and significant and the inclusion of observed firm characteristics increases the coefficient of determination by 6 percentage points. However, the coefficient capturing wage discrimination remains at -0.03, while the female wage penalty is slightly reduced but remains high (the significant coefficient equals -0.18).

The specifications in columns 5 and 6 take into account unobserved time-invariant firm heterogeneity, i.e. some of the differences between firms that could be related to hourly wages (and hourly productivity) and therefore bias the OLS results. The fixed-effect model (column 5) corroborates a small but significant foreigner wage penalty (a 10 percentage point increase in the share of foreigners is associated with a 0.3% decrease in the average wage), but the wage coefficient of women is reduced by 50% to -0.09. Unobserved time-invariant firm heterogeneity appears to be highly correlated with hourly labour productivity since the associated coefficient remains significant but decreases to 0.01. The GMM-IV estimator (column 6) not only takes firm-level heterogeneity into account through its specification in first differences, but also addresses the potential endogeneity of the firm's labour force by using the lagged levels and average industry shares as instruments (see Section III.C). Applying GMM-IV yields a significant and slightly higher wage penalty for both foreigners and women; the corresponding coefficients differ significantly from each other and are equal -0.09 and -0.14, respectively. A series of statistical tests suggests that our instruments are valid and that the model is correctly identified: the model passes the tests for under-, weak- and overidentification (see Section III.C). However, the endogeneity test indicates that the potentially endogenous worker shares can actually be treated as exogenous (the p-value equals 42%), which means that the fixed-effect model should be preferred.

Table 9.3 reproduces Table 9.2 but the estimated models now allow for the respective effects of non-EU men, non-EU women and EU women to differ. Relative to the reference group of EU men, the significant gross wage differential in the parsimonious OLS estimator (column 1) is the highest for non-EU men (a 10 percentage point increase of this group is associated with a 2.9% drop of the average firm wage), followed by non-EU women (-1.2%) and EU women (-0.8%). This order arguably reflects both the sorting of non-EU men into low-productivity firms and the fact that this group has the lowest level of human capital (see Table 9.1). The order is indeed inverted once we control for observed individual and job characteristics (column 2). Segregation into sectors and regions accounts for around 40% of the gross wage penalty for non-EU women (column 3), but is less consequential for non-EU men and EU women.

Adding average hourly productivity and firm-level characteristics to the model slightly reduces the relative wage penalty for non-EU men and EU women (column 4). The GMM-IV estimator (column 6) again passes our identification tests but also rejects the endogeneity of the worker shares so that the fixed-effect estimator (column 5) is our preferred model. It suggests that the ceteris paribus wage penalty is the highest for EU women (an increase in EU-women is associated with a 1% lower hourly wage), followed by the penalty for non-EU women (-0.7%), but the difference between the two coefficients is not statistically significant. By contrast, the wage coefficient for non-EU men equals -0.04 and is significantly lower compared to the penalty against EU women.

Table 9.2. Firm-level wage-setting equation without gender-migrantinteraction.

Log of average wage	OLS (1)	OLS (2)	OLS (3)	OLS (4)	Fixed- (5)	GMM- (6)
Labour productivity	-	-	-	0.10***	0.01**	-0.00
Share of non-EU	-	-0.06***	-0.03**	-0.03***	-0.03***	-0.09*
Share of women	-	-0.23***	-0.22***	-0.18***	-0.09***	-0.14**
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Individual and job	No	Yes	Yes	Yes	Yes	Yes
Sectors and regions3	No	No	Yes	Yes	Yes	Yes
Firm characteristics4	No	No	No	Yes	Yes	Yes
Observations	23712	23712	23712	23712	23712	8333
Adjusted R2	0.06	0.61	0.63	0.69		0.29
Within R2					0.36	
Between R2					0.59	
Underidentification						0.00
Weak identification						75.1
Overidentification test7						0.32
Endogeneity test8						0.42

Data source: SES-SBS 1999-2010.

[1] Omitted reference: share of EU workers.

[2] Individual and job characteristics include share of workers younger than 40 years, share of 8 occupational groups (reference: service occupations); 3 educational levels (reference: ISCED 1-2).

[3] Sector and regional controls include 9 sectors (reference: manufacturing) and 3 regions (reference: Flanders).

[4] Firm controls include the logarithm of firm size and the logarithm of capital. All regressions include year dummies.

[5] Underidentifcation test reports p-value of Kleibergen-Paap rk LM statistic;

[6] Weak identification test reports Kleibergen-Paap rk Wald F statistic;

[7] overidentification test reports p-value of Hansen J statistic.

[8] Endogeneity test shows probability that endogenous regressors can actually be treated as exogenous.

[9] ***,**,* significant at 1, 5 and 10% levels, respectively

[10] HAC standard errors in parentheses.

Wage gap equations

Table 9.4 shows estimates for Equation 3. In the parsimonious OLS estimator (column 1), the parameter $\hat{\gamma}$ is significantly positive and equals 1.37, i.e. a 10 percentage point increase in the share of foreigners is associated with a rise in the native-foreigner wage gap of 14 cents per hour. The coefficient increases to 1.75 when we include individual and job characteristics to the model but decreases once we control for sectoral and regional segregation and firm characteristics. Whereas observed firm characteristics (including average labour productivity) do not exert a significant effect on the wage gap, the inclusion of firm fixed-effects (column 5) increases $\hat{\gamma}$ to 2.88. The coefficient is even higher in the GMM-IV estimator (column 6) which, however, again suggests that the potentially endogenous regressors can actually be treated as exogenous. All specifications that include the share of women yield insignificant coefficients for this variable, indicating that the proportion of women in the firm is not correlated with the average wage gap between natives and foreigners. The last result is contradicted by the estimations in Table 9.5 which include interactions between gender and foreigner status. All models suggest that the share of women is significantly related to the native-foreigner wage gaps, but this effects points in opposite directions for native and foreign women: whereas a 10% increase in non-EU women is related to 60 cent higher hourly wage gaps, a similar increase of EU women lowers the gap by around 10 cents in the OLS model controlling for observables (column 4). This asymmetric effect is further amplified when we control for firm fixed effects (column 5), which is again our preferred estimator given that the endogeneity test in the otherwise valid GMM-IV model indicates that potential endogeneity of worker shares is unproblematic in our data. As a consequence, the data-preferred model suggests that a relatively most increas of 1 percentage point in the proportion of non-EU women in a firm is associated with an increase in the gap between the hourly wages of natives and foreigners of as much as 11.6 cents per hour, which is more than 10% of the average hourly wage gap of 1.06 euros in the entire sample. Conversely, a 1 percentage point increase in the share of EU women displays a downward but much smaller association with the native-foreigner wage gap within firms (2.5 cents). The difference between the coefficients of the two female groups is highly significant, as is their respective difference with the coefficient of non-EU men which is not significantly different from zero in any of the specifications.

Table 9.3. Firm-level wage-setting equation with gender-migrant interaction.

Log of average wage	OLS (1)	OLS (2)	OLS (3)	OLS (4)	Fixed- (5)	GMM- (6)
Labour productivity	-	-	-	0.10***	0.01**	-0.00
Share of male non-EU1	-	-0.08***	-0.06***	-0.05***	-0.04***	-0.07**
Share of female non-	-0.12**	-0.22***	-0.13***	-0.13***	-0.07**	-0.12**
Share of female EU1	-0.08***	-0.20***	-0.22***	-0.19***	-0.10***	-
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Individual and job	No	Yes	Yes	Yes	Yes	Yes
Sectors and regions3	No	No	Yes	Yes	Yes	Yes
Firm characteristics4	No	No	No	Yes	Yes	Yes
Observations	23712	23712	23712	23712	23712	8333
Adjusted R2	0.07	0.61	0.63	0.69		0.29
Within R2					0.36	
Between R2					0.59	
Underidentification						0.00
Weak identification						115.6
Overidentification test7						0.40
Endogeneity test8						0.37

Data source: SES-SBS 1999-2010.

[1] Omitted reference: share of male EU workers.

[2] Individual and job characteristics include share of workers younger than 40 years, share of 8 occupational groups (reference: service occupations); 3 educational levels (reference: ISCED 1-2).

[3] Sector and regional controls include 9 sectors (reference: manufacturing) and 3 regions (reference: Flanders).

[4] Firm controls include the logarithm of firm size and the logarithm of capital. All regressions include year dummies.

[5] Underidentifcation test reports p-value of Kleibergen-Paap rk LM statistic;

[6] Weak identification test reports Kleibergen-Paap rk Wald F statistic;

[7] overidentification test reports p-value of Hansen J statistic.

[8] Endogeneity test shows probability that endogenous regressors can actually be treated as exogenous.

[9] ***,**,* significant at 1, 5 and 10% levels, respectively

[10] HAC standard errors in parentheses.

Table 9.4. Firm-level wage gap equation without gender-migrant interaction.

Wage gap	OLS (1)	OLS (2)	OLS (3)	OLS (4)	Fixed- (5)	GMM- (6)
Labour productivity	-	-	-	0.06	0.08	0.38
Share of non-EU	1.37***9	1.75***	1.26***	1.23***	2.88***	3.14**
Share of women	-	-0.13	-0.11	-0.12	-0.45	-0.85
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Individual and job	No	Yes	Yes	Yes	Yes	Yes
Sectors and regions3	No	No	Yes	Yes	Yes	Yes
Firm characteristics4	No	No	No	Yes	Yes	Yes
Observations	12494	12494	12494	12494	12494	3833
Adjusted R2	0.00	0.01	0.02	0.02		0.02
Within R2					0.02	
Between R2					0.01	
Underidentification						0.00
Weak identification						80.4
Overidentification test7						0.10
Endogeneity test8						0.63

Data source: SES-SBS 1999-2010.

[1] Omitted reference: share of male EU workers.

[2] Individual and job characteristics include share of workers younger than 40 years, share of 8 occupational groups (reference: service occupations); 3 educational levels (reference: ISCED 1-2).

[3] Sector and regional controls include 9 sectors (reference: manufacturing) and 3 regions (reference: Flanders).

[4] Firm controls include the logarithm of firm size and the logarithm of capital. All regressions include year dummies.

[5] Underidentifcation test reports p-value of Kleibergen-Paap rk LM statistic;

[6] Weak identification test reports Kleibergen-Paap rk Wald F statistic;

[7] overidentification test reports p-value of Hansen J statistic.

[8] Endogeneity test shows probability that endogenous regressors can actually be treated as exogenous.

[9] ***,**,* significant at 1, 5 and 10% levels, respectively

[10] HAC standard errors in parentheses.

Table 9.5. Firm-level wage gap equation with gender-migrant interaction.

Wage gap	OLS (1)	OLS (2)	OLS (3)	OLS (4)	Fixed- (5)	GMM- (6)
Labour productivity	-	-	-	0.06	0.03	0.38
Share of male non-EU1	0.08	0.51	-0.01	-0.06	0.42	1.02
Share of female non-	6.02***9	5.76***	5.76***	5.78***	11.59***	16.48**
Share of female EU1	-0.62**	-1.02***	-1.08***	-1.09***	-2.52***	-1.37
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Individual and job	No	Yes	Yes	Yes	Yes	Yes
Sectors and regions3	No	No	Yes	Yes	Yes	Yes
Firm characteristics4	No	No	No	Yes	Yes	Yes
Observations	12494	12494	12494	12494	12494	3833
Adjusted R2	0.01	0.01	0.03	0.03		0.02
Within R2					0.02	
Between R2					0.02	
Underidentification						0.00
Weak identification						33.6
Overidentification test7						0.21
Endogeneity test8						0.76

Data source: SES-SBS 1999-2010.

1 Omitted reference: share of male EU workers.

2 Individual and job characteristics include share of workers younger than 40 years, share of 8 occupational groups (reference: service occupations); 3 educational levels (reference: ISCED 1-2).

3 Sector and regional controls include 9 sectors (reference: manufacturing) and 3 regions (reference: Flanders).

4 Firm controls include the logarithm of firm size and the logarithm of capital. All regressions include year dummies.

5 Underidentifcation test reports p-value of Kleibergen-Paap rk LM statistic;

6 Weak identification test reports Kleibergen-Paap rk Wald F statistic;

7 overidentification test reports p-value of Hansen J statistic.

8 Endogeneity test shows probability that endogenous regressors can actually be treated as exogenous.

9 ***,**,* significant at 1, 5 and 10% levels, respectively

10 HAC standard errors in parentheses.

5. Discussion and conclusion

The work presented in this chapter is one of the first to use firm-level matched employer-employee data and direct information on wages and labour productivity to measure discrimination against foreigners. We build on a recent identification strategy proposed by Bartolucci (2014) that draws on the earlier Hellerstein and Neumark (1999) approach but, among other advantages, does not require committing to a specific functional form of the production function. In addition to addressing econometric issues such as the potential endogeneity of worker shares through a diff GMM-IV estimator, we draw attention to the so far overlooked issue that the Hellerstein-Neumark-Bartolucci approach is based on the implicit assumption of constant wage gaps, i.e. its interpretation of the impact of the share of foreigners on the average firm wage assumes implicitly that the respective average wages of foreigners and natives are insensitive to changes in the share of foreigners. We then assess the implications of this assumption empirically and provide evidence that the average pay gap between native and foreign co-workers measured in a Bartolucci-type wage-setting equation is positive in our sample, but also that this gap is not constant because it is influenced by the composition of the firm with respect to gender and origin, whereas the last two categories are shown to interact in meaningful ways.

Our preferred estimator of a Bartolucci-type wage-setting equation (the fixed-effect model shown in column 5 of Table 9.2) suggests that an increase in the share of non-EU workers in a firm is correlated with a modest but significant decrease of the average wage paid in Belgian firms. Our preferred model including interactions between gender and immigrant status (column 5 in Table 9.3) corroborates modest wage discrimination against men of non-EU origin, but also shows that the wage discrimination against both native and foreign women is significantly higher. Results suggest that origin is not associated with a significantly different wage penalties among women: we therefore find evidence for significant wage discrimination against foreigners and women, but female foreigners do not appear to be exposed to "double-discrimination" by Belgian employers. This result stands up to a series of tests, including measurement issues such as unobserved time-invariant firm heterogeneity, the potential endogeneity of the firm composition, but also to alternative definitions of the immigrant status (see footnote 6 in Section 4.2) and the reduction of our sample to firm-year observations with at least one foreigner per firm (see footnote 8 in Section 4.4). These findings reflect earlier results for Germany by Bartolucci (2014), who also finds negative productivity-adjusted wage coefficients for male and female immigrants as well as native women. The size of wage discrimination found by this study is also relatively modest but somewhat higher compared to our results: a 10 percentage point increase in the share of male foreigners is associated with a 1.3% decrease in the average firm wage in Germany, whereas we find a 0.3% decrease for Belgium. Unlike our estimations, however, Bartolucci (2014) finds evidence for double-discrimination against female foreigners in Germany (a 10 percentage point increase in female foreigners is associated with a 2.7% lower average firm wage).

The wage coefficients in the Bartolucci wage equation are based on the implicit assumption that the wage gap between foreigners and non-foreigners does not change. A negative wage coefficient associated to the proportion of foreigners in a Bartolucci wage equation means that there is a wage gap between foreigners and natives because a negative relationship between the share of foreigners and the average wage in the firm implies that the former group earns on average less than the latter. However, as discussed in Section 3.2, we should be cautious of interpreting the coefficients in firm-level wage setting equations as evidence that "male immigrants receive wages that are between [x] and [y] percent lower than male natives" (Bartolucci 2014: 23). The reason for this is that the average firm wage is sensitive not only to changes in the composition of the firm but also to changes in the relative wages of migrants and non-migrants. In other words, although a negative coefficient in a firm-level wage-setting equation always indicates wage discrimination, the size of the coefficient confounds potential effects of changes in the share of foreigners with simultaneous changes in the relative wages of foreigners and/or natives in the firm.

In order to assess the implications of this assumption, we used the same dataset to estimate the relationship between the proportion of (male and female) non-EU employees and the wage gap between EU and non-EU workers. A fixed-effect model accounting for observables and time-invariant firm heterogeneity (column 5 in Table 9.4) suggests that a 10 percentage point increase in the share of foreigners widens the average gap between EU and non-EU workers by 29 cents, which corresponds to 27% of the average intra-firm wage gap in our sample. This result is compatible with macro-level findings by Dustmann et al. (2013: 166) that immigration decreases wages in parts of the distribution with many migrants and increases the wages of natives in the upper part of the wage distribution. It is also in line with Böheim et al.'s (2012) evidence of a strong negative impact of a worker's own ethnic group size on the individual's hourly wage, as well as Mitaritonna et al.'s (2014: 21) finding that an "increase in the immigrant share in the district seems to have a strong positive effect on the average wage of natives in local firms". Again, distinguishing between men and women underlines the danger of ignoring the gender dimension in research on migration: while the share of non-EU men is not associated with differences in the native-foreigner wage gap, a 1 percentage point increase in the share of foreign women widens the gap by 11.6 cents per hour, which is a very large effect. Our finding that the share of native women is negatively related to the wage gap, is quite intuitive: since women receive relatively lower wages than men, an increase in their share lowers the average wage of native workers in the firm. It should be noted, however, that the equalizing effect on the wage gap of EU women is much smaller compared to the strong inequality-increasing effect associated with the share of non-EU women (the wage gap decreases by only around 25 cents for a 10 percentage point increase in the proportion of native women). This result corroborates Aydemir and Skuterud's (2008: 2) conclusion that only female immigrants are associated with higher within-firm wage gaps.

The combination of these two sets of results calls for a reassessment of existing microeconometric evidence on wage discrimination against foreigners in general and its interaction with gender in particular. Through the lens of Hellerstein-Neumark-Bartolucci wage equation, the category gender is the most powerful predictor of wage discrimination. While foreign men with the same productivity earn significantly less that their native male co-workers, being a women is associated with a significantly higher wage discrimination that does not vary whether the female worker is of foreign origin or not. It is not far from this result to the conclusion that gender is a more important driver of wage discrimination than origin. This, however, would be a misinterpretation. The reason for this is that the origin of female workers has completely opposite effects on the significant wage gaps between foreign and native workers we observe in the average firm: while an increase in the share of foreign women increases this type of wage inequality within firms, native women exert an equalizing (albeit quantitatively smaller) effect on the average wage gap.

These findings provide a promising field of further microeconometric investigation. They notably imply that lower wages against male foreigners and women should not only be analysed with theories that emphasise the particularities of these groups, such as their presence on crowded markets (Cahuc and Zylberberg 2004) or the initial mismatch or downgrading of foreigners (Dustmann et al. 2013: 166). Being a foreiger can influence the wages of both foreigners and non-foreigners, for instance if they allow natives to specialize in non-routine jobs (Ottaviano and Peri 2012; Böheim et al. 2012) or skilled native workers are selected in firms with abundant manual immigrant labour (Mitaritonna et al. 2014: 21). The strong interaction between gender and origin renders such dynamic firm-level wage spillovers even more complex, but could also be a key to make them more intelligible.

PART V – The impact of diversity

CHAPTER 10 - The heterogeneous effects of workforce diversity

1. Introduction

Efficient management of human resources (HR) is a key issue for firms' economic success. It does not only consist in dealing appropriately with single workers' demands, bureaucratic procedures or institutional settings. Properly managing HR also (and perhaps mostly) implies finding the right workforce mix and to make the most of workers' skills. A diverse workforce, with respect to education, experience or physical stamina, is often needed due to the variety of tasks that have to be performed within firms. Labour diversity may also benefit firm productivity if it fosters complementarities (e.g. between high- and low-skilled workers), generates spillovers (e.g. knowledge transfers between more and less experienced workers), makes the workplace more enjoyable (e.g. educational/skills diversity could be appreciated by employees) or stimulates demand (e.g. customers may prefer companies that have a diverse workforce). The downside of diversity, however, is that it may lead to misunderstandings, communication problems, personal conflicts or negative reactions from stakeholders that undermine performance (Akerlof and Kranton, 2000; Becker, 1957; Choi, 2007; Lazear, 1999).

Today's labour force is getting more and more heterogeneous: ageing, migration, women's increased labour participation and technological change are key drivers of this phenomenon (Ilmakunnas and Ilmakunnas, 2011; Kurtulus, 2012; Parrotta et al., 2012a). Moreover, in many countries companies are under legislative pressure to diversify their workforce either through quotas or affirmative action. Workforce diversity has thus become an essential business concern. Firms have to manage diversity both internally (i.e. among management and staff) and externally (i.e. by addressing the needs of diverse customers, suppliers or contractors). As a result, an increasing number of firms employ a 'diversity manager' whose task is to ensure that diversity does not hamper productivity but may contribute to attaining the firm's objectives. From the workers' point of view, labour diversity may also generate benefits or losses. The latter may be the result of a more (or less) enjoyable working environment, but they may also derive from a higher (or lower) wage. According to competitive labour market theory, workers are paid at their marginal revenue products. Hence, if labour diversity affects productivity, it may also influence workers' earnings.

The empirical evidence regarding the impact of labour diversity on productivity is very inconclusive and studies on wage effects are exceedingly rare (Ilmakunnas and Ilmakunnas, 2011). Moreover, findings must often be interpreted with caution because of methodological and/or data limitations. Only few papers examine how the diversity-productivity nexus is influenced by specific work environments. This is problematic since the optimal degree of diversity is likely to depend on the characteristics of the production unit, for instance the knowledge-intensity and technological content of production (Arun and Arun, 2012; Parrotta et al., 2012b; Pull et al., 2012) or the size of the firm (Fiegenbaum and Karnani, 1991; Konrad and Linneham, 1995; Levy and Powell, 1998; Rynes and Rosen, 1995; Stahl et al., 2010).

The aim of EDIPO research in this area was threefold. First, we put the relationship between labour diversity (measured through education, age and gender) and firm productivity to an updated test, using detailed Belgian linked employer-employee panel data for the years 1999-2006. These data offer several advantages. The panel covers a large part of the private sector, provides accurate information on average productivity (i.e. on the average value added per hour worked) and allows to control for a wide range of worker and firm characteristics. It also enables us to compute various diversity indicators and to address important methodological issues such as firm-level invariant heterogeneity and endogeneity (using both the generalized method of moments (GMM) and Levinsohn and Petrin (2003) estimators). A second aim is to examine how the benefits or losses of labour diversity are shared between workers and firms by estimating the impact of diversity on mean hourly wages and productivity-wage gaps (i.e. profits) at the firm level. Finally, we investigate the link between diversity and productivity in different work environments defined by the technological and knowledge intensity (we use three complementary taxonomies developed by Eurostat (2012) and by O'Mahony and van Ark, 2003) and firm size.

The remainder of this chapter is organized as follows. A review of the literature is presented in the next section. Sections 3 and 4 respectively describe our methodology and data set. The impact of workforce diversity on productivity, wages and productivity-wage gaps across work environments is analysed in Section 5. The last section discusses the results and concludes.

2. Review of the literature

There are different economic forces underlying the relationship between workforce diversity and productivity. As highlighted by Alesina and La Ferrara (2005), these forces may derive from: individual preferences (either people may attribute positive (negative) utility to the well-being of members of their own group (of other groups) or they may value diversity as a social good), individual strategies (even when individuals have no taste for or against diversity, it may be more efficient, notably in the presence of market imperfections, to interact preferably with members of one's own group), or the characteristics of the production function (i.e. the complementarity in individual inputs).

Theoretical predictions regarding the optimal workforce composition are mixed. Lazear (1999) follows the production function approach and develops a theoretical model in which a global (i.e. multinational) firm is presented as a diverse (i.e. multi-cultural) team. He argues that labour diversity is beneficial for firm performance if skills and information sets are group-specific. More precisely, he demonstrates theoretically that the gains from diversity are greatest when three conditions are fulfilled: a) individuals have completely disjoint skills and information sets, b) the latter are all relevant for the tasks that have to be performed within the firm, and c) individuals are able to communicate and understand each other.

The organizational demography literature stresses the importance of social similarity for interaction, communication and cohesion among the workforce (Pfeffer, 1985). For instance, diversity in terms of age, education or gender decreases social similarity and could hamper job satisfaction, communication and firm performance. In contrast, social comparison theory posits that people evaluate and compare their opinions and abilities with those of similar others, like individuals of the same age, education or gender (Festinger, 1954). More precisely, individuals may strive to outperform the members of their comparison group (Pelled et al., 1999), which in turn leads to rivalry and conflicts that could undermine organizational performance (Choi, 2007). But social similarity can also be beneficial: a decision may be of better quality when it is the outcome of a confrontation between competing views (Grund and Westergaard-Nielsen, 2008), and rivalry among similar workers may encourage workers to produce more effort in the context of intra-firm ‘tournaments’ (Lazear and Rosen, 1981).

Productivity effects of workforce diversity are likely to vary across work environments (Stahl et al., 2010). In particular, they may differ with respect to the knowledge intensity and high-tech content of the production. Firms which depend on the exploitation of new opportunities and the development of successful innovations may benefit more from diversity than traditional firms (Prat, 2002). The greater complexity of tasks within innovative sectors is also perceived as a feature likely to foster diversity-related benefits (Jehn, 1995; Stewart, 2006): provided that workforce diversity increases the set of ideas and potential solutions to a given problem, it may stimulate the innovative capacity of firms and hence their productivity (Parrotta et al., 2012b). In addition, the HR literature stresses that firms in innovative sectors may benefit from the promotion of diversity as it potentially broadens the talent pool, widens perspectives and enlarges the customer base (Cox and Blake, 1991; Yang and Konrad, 2011).

Productivity effects of workforce diversity may also vary according to firm size. In general, workers are likely to be relatively more responsive to the dissimilarity of their close co-workers with whom they interact more frequently. As a consequence, the effects of diversity might be more pronounced in smaller firms in which all workers interact with each other more often (Stahl et al. 2010) and work organization is less rigid (Fiegenbaum and Karnani, 1991; Levy and Powell, 1998). In bigger firms, the diversity of the entire labour force is probably less likely to trigger productivity effects than diversity within teams or departments in which people interact more often. In addition to the frequency of interactions, another factor related to firm size is the capacity to manage diversity. Smaller firms may be less efficient regarding diversity management as their HR departments (if existent) may typically screen workers less systematically during the hiring process, allocate workers to less optimal positions, face more difficulties to recruit diverse workers (Carrington et al. 2000; Chay, 1998; Holzer, 1998) and devote less resources to diversity management (Konrad and Linnehan, 1995; Rynes and Rosen, 1995). The possibilities to relocate workers inside the company in case of disputes are also likely to be more limited in smaller organizations.

3. Methodology

The method applied in this chapter is an extension of the EDIPO framework presented in Part I of this report. Labour diversity indicators with respect to education, age and gender ($E\sigma$, $A\sigma$ and $G\sigma$) are the main variables of interest. A theoretical model justifying the inclusion of diversity indicators, on top of mean values, in a firm-level productivity equation is provided by Iranzo et al. (2008). The three firm-level diversity indicators used in this paper (i.e. the standard deviation, the average dissimilarity index and the alternative gender diversity index) are conceptually and mathematically relatively similar and can be regarded as robustness tests for our regression results. In particular, all three diversity indicators share the property that diversity is maximal in case of a symmetrical bi-modal distribution with the modes occurring at the extreme values of the attribute under study (i.e. when observations are equally split between the modes); conversely, the minimum of all three indicators is reached when all workers belong to the same group.

4. Data and descriptive statistics

Our empirical analysis is based on a combination of two large data sets covering the period 1999-2006. The first, carried out by Statistics Belgium, is the 'Structure of Earnings Survey' (SES). The SES provides no financial information. It has therefore been merged with a firm-level survey, the 'Structure of Business Survey' (SBS). Our final sample consists of an unbalanced panel of 7,463 firm-year-observations from 2,431 firms. It is representative of all medium-sized and large firms in the Belgian private sector, with the exception of large parts of the financial sector (NACE J) and the electricity, gas and water supply industry (NACE E).

Table 10.1: Descriptive statistics at the firm level (1999-2006)

	All firms		**HT/KIS firms**		**Non-HT/KIS firms**	
Variables	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Hourly wage (€[a])	17.14	5.39	18.38	5.68	16.64	5.18
Value-added per hour (€[a])	61.06	458.61	64.49	239.10	59.71	520.20
Average age (years)	38.42	4.19	37.45	4.35	38.80	4.07
Standard deviation of age	9.33	1.82	9.01	2.01	9.45	1.73
Age dissimilarity index	12.61	2.52	12.16	2.77	12.79	2.39
Average education (years)	11.44	1.76	12.32	1.79	11.09	1.62
Standard deviation of education	1.90	0.84	1.79	0.77	1.94	0.86
Education dissimilarity index	2.54	1.15	2.40	1.05	2.60	1.18
Women (%)	0.27	0.24	0.33	0.25	0.24	0.23
Standard deviation of gender	0.35	0.15	0.38	0.14	0.34	0.16
Gender dissimilarity index	0.46	0.22	0.51	0.20	0.45	0.22
Workers with tenure >= 10 years (%)	0.39	0.24	0.33	0.25	0.42	0.24
White-collar workers (%)	0.45	0.34	0.62	0.36	0.39	0.31
Part-time (< 30h/week, %)	0.02	0.07	0.02	0.06	0.02	0.07
Fixed-term employment contacts (%)	0.04	0.10	0.05	0.12	0.04	0.09
Sector (%)						
Capital stock (€[a])	244,287	2,117,000	489,790	3,946,000	147,644	292,979
Investments (€[a])	18,543	254,447	40,205	476,648	10,019	24,221
Size of the firm (number of full-time equivalent workers)	131.85	336.37	203.76	551.76	116.63	267.12
Number of observations	7,463		2,108		5,355	
Number of firms [b]	2,431		679		1,778	

Notes: [a] At 2006 constant prices. [b] The sum of HT/KIS and non-HT/KIS firms exceeds the total number of firms due to a small number of them changing category during the observation period.

Table 10.1 sets out the means and standard deviations of selected variables. We observe that firms have a mean value added per hour worked of 61.06 EUR and that workers' mean gross hourly wage stands at 17.14 EUR. As regards diversity indicators, we find that the intra-firm standard deviation (the dissimilarity index) reaches respectively 9.33 (12.61) for age, 1.90 (2.54) for education, and 0.35 (0.46) for gender. For comparison, Ilmakunnas and Ilmakunnas (2011) report similar standard deviations (and average dissimilarity indices) for Finland of 10.04 (13.67) for age and 1.93 (2.71) for education.

5. Empirical results

We report findings based on the GMM-SYS and LP estimators. Table 10.2 shows the impact of diversity indicators (the standard deviation and the dissimilarity index, respectively) on productivity, mean wages and productivity-wage gaps at the firm-level.

GMM-SYS estimates are reported in columns (1) to (6). To examine their reliability, we first apply the Hansen and Arellano-Bond tests. For all specifications, they respectively do not reject the null hypothesis of valid instruments and of no second-order autocorrelation in the first differenced errors. Results in columns (1) and (2) suggest that age and gender diversity have a significant negative influence on productivity. More precisely, they indicate that if age diversity increases by one standard deviation, productivity on average decreases by 4 percent. Such a change in diversity is equivalent to an increase in the standard deviation of age of 1.82 years and an increase in the dissimilarity index of 2.52 years. To give a numerical example of a hypothetical firm with four employees, such a change roughly corresponds to a shift from workers aged 25, 40, 45, and 55 years to workers aged 25, 40, 45 and 60 years.

LP estimates, reported in columns (7) and (8), confirm that age and gender diversity appear to be harmful for productivity. Point estimates indeed suggest that an increase in these variables of one standard deviation hampers productivity on average by 1.3 and 1.7 percent, respectively. As regards the coefficient on educational diversity, it is still positive but now also significantly different from zero. More precisely, results suggest that when educational diversity increases by one standard deviation (that is by respectively 0.84 and 1.15 years for the standard deviation and dissimilarity index), productivity on average rises by approximately 2.7 percent. Findings in columns (3) and (4) show that GMM-SYS regression coefficients associated to diversity indices are of the same sign and order of magnitude in the wage and productivity equations. While age and gender diversity are found to depress mean workers' wages, the reverse finding is found for educational diversity. Results in columns (5) and (6) further indicate that educational and gender diversity have a non-significant impact on the productivity-wage gap. Gains (losses) due to educational (gender) diversity thus appear to be shared 'competitively' between workers and firms so that profits remain unaffected. In contrast, age diversity is found to have a stronger negative impact on productivity than on wages. More precisely, results show that an increase of one standard deviation in the age diversity index decreases the productivity-wage gap (i.e. profits) on average by about 2.3 percent

Table 10.2: Estimation results for the entire sample

	GMM-SYS						LP	
	Value added per hour worked (ln)		Mean wage per hour worked (ln)		Value added-wage gap (ln)		Value added per hour worked (ln)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Std. dev. age	-0.022***		-		-0.013*		-0.007**	
	(0.008)		(0.004)		(0.007)		(0.003)	
Age dissimilarity		-0.016***		-0.007***		-0.009*		-0.005*
		(0.006)		(0.003)		(0.005)		(0.003)
Std. dev. education	0.009		0.017**		-0.008		0.032***	
	(0.015)		(0.007)		(0.013)		(0.008)	
Education dissimilarity		0.007		0.012**		-0.005		0.024***
		(0.011)		(0.005)		(0.010)		(0.006)
Std. dev. gender	-0.260**		-0.140**		-0.120		-0.113*	
	(0.102)		(0.055)		(0.094)		(0.064)	
Gender dissimilarity		-0.176**		-0.097**		-0.079		-0.075*
		(0.076)		(0.041)		(0.069)		(0.039)
Average age	0.011***	0.011***	0.009***	0.009***	0.002	0.002	0.010***	0.010***
	(0.003)	(0.003)	(0.001)	(0.001)	(0.003)	(0.003)	(0.002)	(0.002)
Average education	0.077***	0.077***	0.046***	0.046***	0.032***	0.032***	0.075***	0.075***
	(0.007)	(0.007)	(0.003)	(0.003)	(0.006)	(0.006)	(0.006)	(0.005)
Hansen over-identification test, *p*-value	0.765	0.767	0.152	0.172	0.487	0.480		
Arellano-Bond test for AR(2), *p*-value	0.123	0.124	0.370	0.356	0.560	0.561		
Number of observations	7,463	7,463	7,463	7,463	7,463	7,463	7,461	7,463
Number of firms	2,431	2,431	2,431	2,431	2,431	2,431	2,431	2,431

Notes: *** p<0.01, ** p<0.05, * p<0.1. Clustered standard errors are reported between brackets. Regressions also control for: % workers with 10 years of tenure or more, % white-collar workers, % employees with a fixed-term contract, % part-time workers, firm size and capital stock, industries (8 dummies), and years dummies (7). AR(2) refers to second-order autocorrelation in first-differenced errors. GMM-SYS specifications include first and second lags of explanatory variables (except time dummies) as instruments.

Table 10.3: Estimation results for different technological/knowledge environments (HT/KIS nomenclature)

	GMM-SYS						**LP**	
	Value added per hour		**Mean wage per hour**		**Value added-wage**		**Value added per hour**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Std. dev. age	-0.022**		-0.011**		-0.011		-0.001	
	(0.010)		(0.005)		(0.009)		(0.005)	
Age dissimilarity		-0.017**		-0.007**		-0.009		-0.001
		(0.007)		(0.003)		(0.007)		(0.003)
Std. dev. education	0.011		0.001		0.010		0.025***	
	(0.022)		(0.010)		(0.021)		(0.009)	
Education dissimilarity		0.006		0.001		0.019***		0.019***
		(0.016)		(0.007)		(0.007)		(0.007)
Std. dev. gender	-0.327**		-0.172**		-0.155		-0.194***	
	(0.136)		(0.068)		(0.123)		(0.069)	
Gender dissimilarity		-0.230**		-0.119**		-0.112		-0.142***
		(0.100)		(0.050)		(0.089)		(0.039)
Std. dev. age*HT/KIS	0.011		0.006		0.005		-0.014	
	(0.026)		(0.012)		(0.024)		(0.009)	
Age dissimilarity*HT/KIS		0.011		0.004		0.007		-0.010
		(0.019)		(0.009)		(0.017)		(0.007)
Std. dev. education*HT/KIS	-0.007		0.039*		-0.047		0.033	
	(0.056)		(0.022)		(0.049)		(0.024)	
Education		-0.001		0.026		-0.028		0.023
		(0.040)		(0.016)		(0.034)		(0.017)
Std. dev. gender*HT/KIS	0.716*		0.174		0.542		0.343**	
	(0.398)		(0.139)		(0.361)		(0.147)	
Gender dissimilarity*HT/KIS		0.527*		0.121		0.406		0.261***
		(0.283)		(0.102)		(0.255)		(0.091)
Average age	-0.005	-0.003	0.003	0.003	-0.008	-0.006	0.008***	0.008***
	(0.016)	(0.016)	(0.008)	(0.008)	(0.014)	(0.014)	(0.003)	(0.003)
Average education	0.055	0.048	0.002	0.002	0.053	0.046	0.063***	0.064***
	(0.043)	(0.042)	(0.020)	(0.019)	(0.040)	(0.039)	(0.005)	(0.007)
Average age*HT/KIS	0.035*	0.034	-0.001	-0.000	0.036**	0.034*	0.006	0.006
	(0.021)	(0.021)	(0.010)	(0.010)	(0.018)	(0.018)	(0.004)	(0.004)
Average education*HT/KIS	0.066	0.073	0.064**	0.062**	0.002	0.011	0.037***	0.037***
	(0.064)	(0.064)	(0.029)	(0.029)	(0.053)	(0.052)	(0.010)	(0.013)
HT/KIS	-2.552***	-2.635***	-0.934**	-0.896**	-1.618*	-1.739**	-0.691***	-0.689***
	(0.981)	(0.972)	(0.453)	(0.452)	(0.868)	(0.860)	(0.213)	(0.212)
Hansen over-identification test,	0.177	0.192	0.055	0.065	0.334	0.306		
Arellano-Bond test for AR(2), p-	0.117	0.116	0.458	0.442	0.499	0.502		
Number of observations	7,463	7,463	7,463	7,463	7,463	7,463	7,461	7,463
Number of firms	2,431	2,431	2,431	2,431	2,431	2,431	2,431	2,431

Does the technological/knowledge environment matter?

HT/KIS nomenclature

The diversity-productivity-wage nexus is likely to vary across different work environments. Various theoretical arguments (reviewed in section 2.2) suggest in particular that the former may differ between knowledge intensive sectors and more traditional industries. Given the scarcity of empirical evidence on this issue, in this section we first present estimates of our model for two distinct types of firms: those belonging to high-medium tech/knowledge intensive sectors (HT/KIS) and those that do not.

Applied to our sample, this taxonomy classifies 679 firms as HT/KIS and 1,778 as non-HT/KIS firms. As shown in Table 10.1, these two types of firms differ along several dimensions. Both the average hourly value added and wage are higher in HT/KIS compared to non-HT/KIS firms, confirming the intuition that HT/KIS firms are in general more productive. Moreover, HT/KIS firms are found to have a significantly larger capital stock and to invest more. Differences in age, educational and occupational composition also exist: the workforce of HT/KIS firms is on average much more concentrated in white collar occupations (62 vs. 39 percent), somewhat more educated and slightly younger compared to non-HT/KIS firms. Interestingly, HT/KIS firms are also characterised by a more feminine labour force (33 vs. 24 percent). Both HT/KIS and non-HT/KIS employment is predominantly concentrated in the manufacturing sector (respectively around 53 and 59 percent). Yet, while almost 40 percent of HT/KIS employment is found in real estate, renting and business activities and financial intermediation, about a third of non-HT/KIS workers is employed in the construction and wholesale and retail trade industry (including repair of motor vehicles, motorcycles and personal and household goods).

Results based on GMM-SYS and LP estimators are reported in Table 10.3. The reliability of GMM-SYS estimates is supported by the outcomes of the Hansen and Arellano-Bond tests. For all specifications, they respectively do not reject the null hypothesis of valid instruments and of no second-order autocorrelation in first differenced errors.

Overall, GMM-SYS and LP estimates again suggest that age (educational) diversity is detrimental (beneficial) for firm productivity. Moreover, given that interaction effects with the HT/KIS dummy variable are systematically insignificant, it appears that the size of the elasticity between productivity and diversity in age and education does not depend on firms' technological environment and knowledge-intensity. Furthermore, results indicate that age and educational diversity have a similar impact on wages and productivity. On the whole, they thus suggest that profitability (i.e. the productivity-wage gap) does not depend on the diversity of the workforce in terms of education or age.

We find remarkable results regarding the consequences of gender diversity on productivity. Indeed, while gender diversity is still found to hamper firms' productivity in more traditional sectors, firms belonging to high-medium tech/knowledge intensive sectors appear to be significantly more productive when employing a more gender-balanced workforce. More precisely, estimates suggest that if gender diversity – measured respectively through the standard deviation and dissimilarity index – increases by one standard deviation, productivity increases (decreases) on average by between 2.5 and 6 percent (3 and 5 percent) in HT/KIS firms (non-HT-KIS firms). Besides, results show that gender diversity has no significant influence on the productivity-wage gap in both types of environments.

6. Discussion and conclusion

This paper estimates the impact of workforce diversity (in terms of education, age and gender) on productivity, wages and productivity-wage gaps (i.e. profits). It contributes significantly to the existing literature as it is one of the first: i) to use large representative data (i.e. Belgian linked employer-employee panel data covering most private sector firms over the period 1999-2006), ii) to address important methodological issues such as firm-level invariant heterogeneity and endogeneity, iii) to examine how the benefits or losses of labour diversity are shared between workers and firms (i.e. to extend the analysis to wages and productivity-wage gaps), iv) to investigate whether the diversity-productivity-wage nexus depends on the degree of technological/knowledge intensity of firms, v) to test whether results vary according to firm size.

Findings, based on the generalized method of moments (GMM) and Levinsohn and Petrin (2003) estimators, show that educational diversity is beneficial for firm productivity and wages. In contrast, age and gender diversity are found to hamper firm-level added value and average earnings. The magnitude of these effects is relatively big: estimates notably suggest that when age or gender diversity (educational diversity) increases by one standard deviation, productivity drops (rises) on average by around 4 percent (almost 3 percent). Yet, the consequences of gender diversity are found to depend on the technological/knowledge intensity of firms. Gender diversity generates gains in high-tech/knowledge intensive sectors: productivity is found to rise on average by between 2.5 and 6 percent following a one standard deviation increase in gender diversity. The reverse result is obtained in more traditional industries. Overall, findings do not point to sizeable productivity-wage gaps associated with educational and gender diversity. Age diversity, on the opposite, is generally found to decrease firm's profitability.

Belgium is no exception regarding the labour market trends that affect diversity (ageing, increase in education levels and female labour market participation) in most OECD countries. Our estimations for Belgium suggest that the effects of these changes are also similar to those found in other economies. Results are notably in line with those obtained for Denmark by Parrotta et al. (2012a) showing a negative effect of demographic diversity (age, gender and ethnicity) and a positive one of educational diversity. Also Navon (2009) finds a positive effect of education diversity in Israel. Negative effects of age diversity are also in line with those found for the U.S. at company level by Hamilton et al. (2004), Kurtulus (2011) and Leonard and Levine (2013). The latter also find insignificant (or no substantial) evidence of the impact of gender diversity on sales, which is similar to our results for profits that do not account for the knowledge intensity of firms (gender diversity is significant in high-tech/knowledge intensive sectors). Our findings only contrast with those of Ilmakunnas and Ilmakunnas (2011) for Finland who show a positive effect of age diversity and a negative one of educational diversity.

How can these findings be interpreted? Results from our benchmark specification showing that educational (age and gender) diversity improves (hamper) firm productivity are consistent with the theoretical predictions of Lazear (1999) and Jehn et al. (1999) highlighting that diversity benefits productivity if the gains of a more diverse workforce in terms of complementary skills and information sets outweigh additional costs related to communication and conflicts. Moreover, they argue that this condition is unlikely to be satisfied for demographic diversity (heterogeneity in terms of e.g. age and gender) but may well be fulfilled for educational (i.e. task related) heterogeneity. In line with our results, they indeed suggest that mutual learning and collaboration among workers with different educational backgrounds may be sufficient to enhance efficiency. Results for gender and age diversity are more in line with the conclusions of the organizational literature (see e.g. Pfeffer, 1985), which emphasize the importance of social similarity (notably in terms of gender and age) to stimulate interaction, communication and cohesion among the workforce.

Interaction effects between gender diversity and the technological/knowledge environment of firms can be reconciled with the predictions of Prat (2002) and Jehn et al. (1999). The latter argue that the benefits of diversity are more likely to exceed the costs when the work environment is predominantly characterized by complex (rather than routine) tasks, negative complementarities (i.e. workers' actions are substitutes in the firm's payoff function) and innovative (rather than functional) output. Given that these features are more likely to be encountered in high-tech/knowledge intensive sectors than in more traditional industries, they may contribute to the explanation of our results. Although our approach differs from Kurtulus (2011) in that we look at diversity effects in different sectors while Kurtulus assesses the impact of diversity in different occupational groups (finance, marketing, operations, etc) within the same establishment, our findings are analogue to Kurtulus' observation that "it is evident that the impact of worker dissimilarity on worker performance is quite different for workers in different occupations".

Overall, our results regarding the impact of gender and educational diversity on the productivity-wage gap suggest that gains and losses associated with diversity are shared 'competitively' between workers and firms so that profits remain unaffected. In contrast, firm profitability is found to depend negatively on age diversity. According to Cataldi et al. (2012), older (younger) workers tend to be 'over-paid' ('under-paid') in Belgian private sector firms. Hence, the negative effect of age diversity on profitability is likely to derive from the fact that: i) increases in age diversity are essentially the consequence of an aging workforce, and ii) the 'over-payment' of older workers may outweigh the 'underpayment' of younger workers (as suggested by Cataldi et al., 2011).

While diversity is thought to be beneficial in much of the literature in HRM, our findings suggest that in certain cases diversity may be detrimental for both companies and workers. Moreover, consequences of diversity are found to substantially depend on the firm's environment: production in high-tech/knowledge intensive sectors is more likely to benefit from gender diversity than those in more traditional industries. Accordingly, the latter could learn from best practices implemented in the former to make gender diversity work. More generally, personnel measures aimed at improving the impact of age diversity on economic outcomes deserve special attention.

CHAPTER 11 - What are the effects of diverse work contracts in Belgium?

1. Introduction

A nuanced understanding of the different repercussions of fixed-term employment contracts (FTCs) has emerged as an increasingly salient problem in labour economics and the study of employment relations. In the 1980s and 1990s, FTCs were widely regarded as a potent tool for injecting more flexibility into ossified labour markets. They also seemed to fit better to the Japanese 'lean production' model that replaced traditional inventory-heavy models in many advanced economies in the 1990s (Dhyne and Mahy, 2012). Eager to adapt labour markets to an apparent demand for more flexibility, legislators in most industrialised economies relaxed laws regarding temporary employment (Bentolila and Bertola 1990; Mahy 2005) and the average share of FTCs in OECD countries increased from 9.2 % in 1980 to 10% in 1990; by 2000 the share reached 11.3%. But over the past 15 years, the FCTs' promise of more flexible and efficient labour markets seems to have lost some of its sparkle. Since the late 1990s, the OECD average of FCTs ceased to grow and oscillated between 11 and 12%; compared to 2003, the proportion of FCTs in 2013 has even declined in countries as different as Belgium, the Czech Republic, Denmark, Finland, Greece, Japan, Korea, Norway, Spain and Turkey. While there is an extensive literature on the many issues related to the flexibilisation of employment relations – with a central strand going back to theories of labour market dualization developed in the 1970s (Piore 1978, Boeri 2011) – this paper sets out to address three key questions related to FCTs that the literature has so far not treated frontally.

What is the relationship between FCTs and productivity?

There is no shortage of theoretical speculations regarding the impact of FCTs on productivity. Most importantly, temporary contracts have been interpreted as a buffer for product demand fluctuations and therefore as vectors of higher labour productivity over the entire business cycle (Jahn et al., 2012). Unfortunately, only few studies have actually been able to measure accurately productivity differences between temporary and permanent workers. As a consequence, the relationship between FTCs and productivity has not been clearly established and the few existing empirical studies are inconclusive (Cappelari et al. 2012; Damiani and Pompei 2010; Dolado and Stucchi 2008; Nielen and Schiersch 2012; Roux and Leclair 2007). A serious deficiency of these studies is that some of them fail to control for estimation biases related to the potential endogeneity of FCTs and the state dependency of profits. By contrast, our paper is one of the first to measure how FTCs affect firm-level productivity by using a generalized method of moments (GMM) estimator that allows us to account for firm-level invariant heterogeneity, endogeneity and state dependence. Our estimates are based on detailed linked employer-employee panel data from Belgium for the years 1999-2010 that covers most of the private sector; provides accurate information on average productivity (i.e. the average value added per hour worked); and includes a wide range of worker and firm characteristics.

How do FCTs affect wages?

A growing literature examines the impact of employment contracts on wages. Empirical results typically document a significant gap between employees with FTCs and permanent contracts (PCs). This gap has been attributed to substantial heterogeneity across jobs and/or individuals (Bosio 2009; Brown and Sessions 2003; Comi and Grasseni 2012; De la Rica 2004). Yet a significant fraction of this gap remains unexplained after controlling for observable heterogeneity. This may suggest discrimination against workers with FTCs but could also be linked to unobserved productivity differences related to FTCs and PCs. In this paper we not only shed new light on the impact of temporary employments on wages by measuring wages equations with matched employer-employee panel data; we are also able to measure potential differences between productivity and wages by estimating productivity and wage equations simultaneously. In other words, we extend the analysis of FTCs to firm competitiveness.

The remainder of the chapter is organized as follows. A review of the literature regarding the relationship between employment contracts, wages and productivity is presented in the next section. The following two sections describe respectively our methodology and data set. We then measure the impact of FTCs on productivity, wages and productivity-wage gaps across industries and discuss our results. The final section concludes.

2. Theoretical and empirical background

Most theories predicting productivity-wage gaps are formulated without specific reference to employment contracts. In this section, we show how the most prominent of these theories can be adapted to account for differences between FCTs and PCs.

Human capital

A first set of explanations that can be applied to the relationship between FTCs, wages and productivity are theories of compensating wage differentials, such as human capital theory and hedonic wage theory. Human capital theory posits that employers might be more reluctant to invest in training for FTC workers if the shorter employment period of the latter means that they benefit less from on-the-job training (Bassanini et al. 2007). Various studies confirm this prediction and suggest lowers investments in human capital for FCT employments (Arulampalam and Booth 1998; Booth et al. 2002; Fouarge et al. 2012). Other authors show that FTC workers are generally less qualified and over-represented among young people, which is in line with their lower labour market experience and tenure (see Eurostat 2012). According to human capital theory, these factors should lead to lower relative productivity and hence wages for FTC workers, which is confirmed by empirical results for Spain showing that diversity in observed skills explains more than 50% of wage differentials between FTC and PC workers (De la Rica 2004). Using a panel of Italian private sector firms, Cappellari et al. (2012) find that the deregulation of FTCs in the early 2000s led to productivity losses. By contrast, Nielen and Schiersch (2012) show, on the basis of a large dataset of German manufacturing firms, that FTCs have no significant effect on labour productivity. It should be noted that human capital differences between FTC and PC workers does not necessarily affect the profitability of firms if workers are paid according to their marginal product.

Asymmetric information and screening

Information asymmetry regarding the quality of labour is also potentially relevant for explaining FTCs. For instance, workers hired on FTCs could be more productive than their colleagues with permanent contracts if the former wish to send a positive signal to their employer so as to increase the likelihood of obtaining a permanent contract (Dhyne and Mahy 2012). Engellandt and Riphahn (2005) corroborate this prediction using Swiss data and find that being on a FTC increases the probability of doing unpaid overtime by about 60%. Moreover, Dolado and Stucchi (2008) show that temporary workers in Spain provide more effort in firms in which the transition rate from a temporary to a permanent contracts is higher. A complementary 'screening' argument is that firms offering PCs only to the most productive FTCs will increase their productivity (Nielen and Schiersch, 2012). Tournament theory has formalised this relationship and argues that firms deal with asymmetric information through performance-related tournaments in which a prize is attributed to the most productive worker (Lazear and Rosen, 1981). This system aims to trigger competition and to encourage workers to provide sustained effort in order to obtain the prize. It is fully conceivable that employers use permanent contracts as a prize in tournaments among workers on FTCs.

Demand fluctuations and adjustment costs

A prominent interpretation of the use of FTCs is that they allow firms to adjust their workforce to business-cycle fluctuations at relatively low termination costs (Nielen and Schiersch 2012). Nunziata and Staffoli (2007) developed a model in which the probability of using FTCs depends on the volatility in product demand. This relationship is backed up by empirical evidence (Houseman 2001; Vidal and Tigges 2009). In general, labour adjustment costs (i.e. hiring and separation costs) play a potential role for the productvity and wages of FCTs. In dynamic labour demand models, adjustment costs are considered as 'quasi-fixed' and amortized over a worker's average length of service within a firm so that workers are no longer paid according to their marginal productivity (Oi 1962). Given that adjustment costs (notably firing costs) are generally lower for FTC workers (Dhyne and Mahy 2012), this model predicts that the gap between productivity and wages is larger for PC workers. This being said, Nielen and Schiersch (2012) note that the flexibility of FTC employments is imperfect because dismissing FTC workers without lay-off costs is only possible at the end of employment contracts.

Collective bargaining

In most advanced economies, temporary workers are less likely to be affiliated in a trade unions than workers on permanent contracts (Salvatori 2009). Trade unions may thus be more willing to defend the interests of the latter, notably with respect to wages (Manning, 2003). Moreover, temporary workers may also suffer from a wage penalty if firms compensate wage increases for permanent workers by imposing wage restraints for temporary employees (Heery 2004). Brown and Sessions (2003) find empirical evidence for wage discrimination against FTC workers in the UK, highlighting that union coverage only improves wages of permanent workers. Jimeno and Toharia (1993) find that FTC employees in Spain perceive lower wages than their permanent counterparts after controlling for observable individual and job characteristics. Their estimates also suggest that wages grow faster in industries in which the proportion of FTC workers is bigger. In line with dual and insider-outsider labour market theories (Piore 1978; Lindbeck and Snower 1986), the authors explain their findings by noting that PC workers' employment protection and bargaining power increase with the share of FTCs as the latter effectively function as a buffer during economic downturns.

Sectors

Sectors are often considered to differ with respect to the two previous dimensions, i.e. the extent of product demand fluctuation and collective bargaining. This suggests that the incidence of FTCs and their productivity relatively are higher in sectors with stronger product demand fluctuations – especially in activities that do not allow for the creation of stocks such as in restaurants or hotels. Moreover, in sectors with low collective bargaining the differences between FTCs and PCs in terms of productivity and wages should be relatively less pronounced. Results by Roux and Leclair (2007) based on French firm-level panel data indeed suggest that the relationship between temporary employment and productivity varies across industries: while temporary employment is found to enhance productivity in services, the impact turns out to be insignificant in the manufacturing industry. However, using sector-level data covering 16 European countries, Damiani and Pompei (2010) show that FTCs in labour-intensive sectors, such as services, discourage human capital investments and deteriorate multifactor productivity. The latter also suggest that employers have to compensate the greater harshness of temporary jobs by a higher wage so that the latter get filled.

3. Results

OLS estimates should be considered with caution due to potential biases regarding firm-level fixed effects, endogeneity and state dependency. To account for these issues, we have estimated with a dynamic GMM-SYS estimator. Estimates are reported in Table 11.3. To assess their reliability we applied Hansen and Arellano-Bond tests. For all regressions, we do not reject respectively the null hypotheses of valid instruments and of no second order auto-correlation in the first-differenced errors. Contrary to the OLS estimates, GMM-SYS results suggest that changes in the shares of FTC workers are not significantly related to productivity, wage costs or profits.

Table 11.1: Entire sample, GMM-SYS estimates

	GMM-SYS [d]		
Dependent variables:	Value added per hour worked (ln) (1)	Labour cost per hour worked (ln) (2)	Profit per hour

			worked (ln) [e] (3)
Lagged dependent variable (ln)	0.655***	0.447***	0.539***
	(0.057)	(0.135)	(0.047)
Fixed-term contracts	0.061	-0.027	0.156
	(0.052)	(0.038)	(0.189)
Worker characteristics [a]	Yes	Yes	Yes
Firm characteristics [b]	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Hansen J statistic	620.0	639.2	586.91
p-value	0.27	0.12	0.63
Arellano-Bond statistic (AR2)[c]	1.52	0.94	1.30
p-value	0.13	0.35	0.14
Number of observations	6,714	6,714	6,714
Number of firms	1,844	1,844	1,844

Notes: *** /**/* significant at 1%, 5%, and 10% level, respectively. Robust standard errors are reported between parentheses.
[a] Share of the workforce that: (i) has at most lower secondary education and a degree from tertiary education, respectively, (ii) has at least 10 years of tenure, and (iii) is younger than 25 and older than 49 years, respectively, (iv) is female, (v) works part-time, and (vi) occupies blue-collar jobs.
[b] Firm size (i.e. number of full-time equivalent workers), capital stock, the level of collective wage bargaining (1 dummy), sectoral affiliation (8 dummies) and, region where the firm is located (2 dummies).
[c] AR2 displays the test for second-order autocorrelation in the first-differenced errors.
[d] First and second lags of explanatory variables, including time dummies, are used as instruments.
[e] ln(profit per hour worked) = ln(value added per hour worked – wage cost per hour worker).

Sector-specific estimates

In this section we present estimates that account for potential heterogeneity of the impact of FTCs across different sectors of activity. Separate GMM-SYS coefficients for industry and services are reported in Table 4. While the coefficients for the sample of industrial firms remain statistically insignificant, GMM-SYS coefficients for the sample of firms in service sector suggest a significantly positive relationship between FTCs and hourly productivity: a one percentage point increase in the share of FTCs is on average associated with a 0.28% rise in hourly value added. The impact of temporary jobs on labour costs and profits is also found to be positive albeit not statistically significant at conventional probability levels.

Table 11.2: Industry (NACE codes C to F) vs. Services (NACE codes G to K), GMM-SYS estimates

	GMM-SYS [d]					
Dependent	**Value added**		**Wage cost**		**Profit per hour**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Lagged dependent	0.641***	0.555***	0.514***	0.374***	0.518***	0.524***
Fixed-term contracts	0.067	**0.276***	0.026	0.094	0.220	0.302
Worker characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Firm characteristics [b]	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Hansen J statistic	503.43	336.36	502.53	338.02	499.21	260.41
Arellano-Bond statistic	1.20	1.41	0.79	0.85	0.90	1.60
Number of	4,511	2,015	4,511	2,015	4,511	2,015
Number of firms	1,143	693	1,143	693	1,143	693

Notes: *** /**/* significant at 1%, 5%, and 10% level, respectively. Robust standard errors are reported between parentheses.

[a] Share of the workforce that: (i) has at most lower secondary education and a degree from tertiary education, respectively, (ii) has at least 10 years of tenure, and (iii) is younger than 25 and older than 49 years, respectively, (iv) is female, (v) works part-time, and (vi) occupies blue-collar jobs.

[b] Firm size (i.e. number of full-time equivalent workers), capital stock, the level of collective wage bargaining (1 dummy), sectoral affiliation (8 dummies) and, region where the firm is located (2 dummies).

[c] AR2 displays the test for second-order autocorrelation in the first-differenced errors.

[d] First and second lags of explanatory variables, including time dummies, are used as instruments.

[e] ln(profit per hour worked) = ln(value added per hour worked – wage cost per hour worker).

The distinction between industry and services is of course relatively crude since it masks potential variations within each of these two macro-secors. To refine the analysis, we have estimated separate regressions for more detailed sectors, namely NACE codes C and D (i.e. mining, quarrying and manufacturing), F (construction), I and J (Financial intermediation; Transport, storage and communications), and G, H and K (Wholesale and retail trade, repair of motor vehicles, motorcycles and household goods; Hotels and restaurants; and Real estate, renting and business activities). These categories arguably reflect fundamental differences in production processes as well as variations in the labour intensity across sectors, while at the same time allowing for sufficiently large subsamples required for the estimation of GMM-SYS coefficients.

The regression results for these sector-level coefficients confirm the absence of a sizable FTC impact in industrial firms: the cofficients in both NACE C-D and NACE F sectors are not significantly different from zero. This is also the case for the service sectors NACE I-J but not for the service sectors G-H-K. Indeed, GMM-SYS estimates suggest that FTCs in the latter services sectors enhance productivity, have no significant effect on labour costs, and consequently improve firms' profitability: a one percentage point increase in the share of FTCs is associated with a 0.48% rise in the gap between hourly productivity and wage costs.

4. Conclusion

Our results suggest that the observed stagnation of temporary employments, or even decline in countries like Belgium, could reflect profit-maximising behaviour of firms: for the economy as a whole, we find no significant evidence for an effect of a firm's use of temporary employments on its average labour productivity or labour costs. Instead of delivering productivity-enhancing flexibility as expected by many policy makers in the 1990s, having a larger share of the workforce on temporary employments does not appear to have a sizeable impact for the average firm.

However, the paper also provides empirical evidence for the dangers of reasoning in terms of the average firm. The latter of course does not exist as each organisation differs in terms of its historical development, current composition and future growth potential. Many of the theoretical arguments against and in favour of temporary employment tend to be linked to specific aspects of a firm's production process, such as its capacity of creating stocks to absorb fluctuations in product demand, the length of necessary on-the-job training or the possibility to screen new employees for talent and motivation. The sectoral differences in the incidence of temporary employment suggest that some of these factors are clustered within certain sectors of activities. Similarly to Roux and Leclair (2007) and Specchia and Vandenberghe (2013), our estimation results indeed suggest that productivity-enhacing effects can be observed in the service sector. Moreover, our evidence suggests that the heterogeneous effects of temporary employments are due to differences in production processes: positive productvity effects and firm rents are concentrated in subsectors that are more labour intensive, use less sophisticated technology and are less able to create stocks, as is the case in NACE sectors G-H-K dominated by retail, hotel and restaurants and business services. These sectors also display the highest incidence of temporary employments in Belgium.

GENERAL CONCLUSION

The research project at the origin of this report aimed at assessing the situation of groups among the population known for being confronted to labour-market barriers, displaying low employment rates, high unemployment rates and a higher-than-average risk of poverty due to wage inequality. These groups comprise, among others, women woking part-time, low-educated individuals and residents of non-EU origin. More precisely, the objectives ot this project was to assess their situation in terms of i) employability, ii) wage discrimination and iii) relative wage.

From a methodological point of view, the novelty of the research summarized in the 11 Chapters forming the backbone of this report, lies, to a large extent, in the use that has been made of matched employer-employee data. The originality of the project is also the strong focus on direct firm-level measure of labour productivity, in order to better assess the situation of these at-risk groups.

The bulk of the existing economic research on the sociodemographic groups facing employment barriers is based on the study of individual-level data: cross-sectional or panel surveys like the EU-LFS, EU-SILC, SHARE, UNECE, administrative sources like the CARREFOUR datawarehouse or the censuses. These data sources provide detailed information about individuals (in terms of their labour market outcomes and their individual/family background, or their productivity-related characteristics: highest degree, labour market experience…). But they suffer from their excessive focus on individuals who represent only the supply side of the labour market, ignoring the role of the demand side: the one of firms. In many works too little is said about the attitude of firms vis-à-vis these groups and its determinants. We have too little robust evidence regarding how these individuals perform inside firms - as a group - and in interaction with other types of workers, capital… When it comes to productivity (which is key to determining employment and wage prospects – see Chapter 1), the existing studies underscore the fact that productivity is, in essence, a firm-level phenomenon. Individual workers' productivity is hardly ever observed. What is more, it is probably intrinsically determined by the (heterogenous) ability of firms to successfully aggregate individual productivities, in interaction with other tangible and intangible production factors (capital, ICT, knowledge, management tools…).

The key hypothesis underpining the research works exposed and summarizd here is that both the demand side (employers) and the supply side (employees) need to be considered simultaneously to better understand problematic labour-market outcomes and identify better policy responses to tackle them. Following that principle, most of the works exposed in this report use of matched employer-employee data sets.

Another aim of the research was to try to deploy a robust firm-level analysis of the relationship between human capital and productivity, wage and employability, in particular of those belonging the above-listed at-risk groups. There is plenty of individual-level evidence, based on the estimation of Mincerian equations, showing that better-educated individuals earn more. Some macroeconomists, analysing cross-country time series, also support the idea that the continuous expansion of education has contributed positively to growth. Surprisingly, most economists with an interest in human capital have neglected the level of the firm to study the education-productivity-wage nexus. The purpose of several of the works presented in this report was to try to fill that void.

On many counts, the numerous researchers involved in the project have delivered results that are methodologically robust — and the number papers published/closed to being published in peer-review international journals support this— , and also very relevant for policy-makers and stakeholders. In this conclusion section we just emphazise a couple of them and we spell out their interest for policymaking.

First, the workers of foreign origin. Their labour-market outcomes is of crucial importance for a country like Belgium. Immigrants make up one fifth of the Belgian working age population, but their labour market integration remains poor. One of the OECD's first and salient observation with respect to the labour market integration of immigrants in Belgium are « the large gaps in the employment of immigrants compared to the native-born in international comparison » (OECD, 2008). The work presented in this report (Chapter 9) is one of the first to use firm-level employer-employee data and direct information on wages and labour productivity to measure discrimination against workers of foreing origin. The authors provide empirical evidence that the average pay gap between native and foreign co-workers is not reductible to productivity difference between the two groups; meaning there is wage discrimination based on the orign inside Belgian private-economy firms. The authors also show that it is mainly men of foreign origin who suffer from wage discrimation. Among women – who are collectively wage discriminated compare to men – the foreing origin is not associated with a significantly penalty. Female foreigners do not appear to be exposed to "double-discrimination" by Belgian employers. In terms of policy this suggest that efforts improving the labour market performance of immigrants requires a many-fold strategy.

Policies aimed at boosting immigrants labour-market outcomes need to be enhanced. The education system needs to become more responsive to the needs of the children of immigrants. Immigrants need more support to develop and validate their human capital, and employers, both public and private, need stronger incentives to hire a more diverse workforce. What the results presented in this report show is that there is also room for anti discrimination efforts inside firms.

Second, part-time and female work. Over the past three decades, part-time jobs have become a prominent feature of many structural labour market changes in Europe and North America, and different scholars have identified part-time employment as one of the main factors underpining economic flexibility. But part-time work remains predominantly female. It raises issues linked to gender equality and the way in which contemporary societies organize the reconciliation of job market participation with non-market activities. It is also related to the poverty agenda. Low-educated, part-time workers that tend to concentrate into sectors and occupations known for being less remunerative are at greater risk of poverty than the other groups of workers. The authors of this report (Chapter 5) confirm the importance of distinguishing men and women regarding part-time work, but also to consider the employers' side. For the latter, part-time work (particularly of the long type) seems to be a working arrangement synonymous of higher (gross) profit margin : when people work long part-time jobs, productivity exceeds pay. This may explain the relative enthousiams of employers for part-time and similar forms of work arrangements, synonymous of flexibility in a less and less predictible economic environement. This being said the origin of these producivity/labour cost gaps differ by gender, with potentially different consequences in terms of the welfare of men and and women. For the group of male workers, particularly in long part-time jobs (>20 hours/week) , the gap is related to a higher hourly productivity (relative to full-time male peers) that is not reflected in their hourly wages (that remains the same as their full-time male colleagues). By contrast, female workers in (any type of) part-time jobs display the same productivity per hour as their full-time (female) peers, but earn lower hourly wages. Hence female part-time work is more likely to generate precarity.

The quick and easy answer could be to recommend that women work more systematically full time. However, many part-time workers – especially women – have no desire to work full-time. Surveys invariable show that large segments of the female population prefer working part-time. This calls, among many other things, for a better understanding of the reasons underpining the deterioration of hourly pay women get when working part-time, and also the identification of the most effective way of avoiding poverty. Could it be that employers are particularly prejudiced against women when they work part-time? Or is it training is less frequent particulary in the sort of jobs accomplished by women working part time? As to anti-poverty policy, is it that women working part-time earning low hourly wages need in-work transfers? Answering these questions goes beyond what can reasonably be done with the evidence gathered in this report. But the latter clearly invites policy-makers to pay attention to the development of the part-time, low paid, and mostly female segment of the labour market.

Third, education. As stated above, there exists substantial micro and macro evidence, based that general education (schooling) increases wages and it good for growth in the long run. These results generally interpreted as a validation of human capital theories where more educated individuals are more productive (and thus better paid, assuming market remunerate production factors according to their marginal productivity). The puzzling element of that approach is that labour productivity is never measured or estimated. It is inferred from variation of wages/remunerations under the assumption that wage differences must reflect productivity differences. What the authors of this report do is to look at firm-level evidence (eg. in Chapter 6) to assess the actual relation between (initial) education, frim productivity and labour costs (reflecting wages). To that aim, they tap into a rich, firm-level, Belgian panel database that contains information on productivity, labour cost and the workforce's educational attainment. The main results suggest that human capital, in particular larger shares of university-educated workers inside firms, translate into significantly higher firm-level labour productivity, and that labour costs (and thus wages) are relatively well aligned on education-driven labour productivity differences. This result has booth theoretical and policy implications. From a theoretical point of view, the result constitue a validation of the textbook version of the human capital theory : more education lead to higher wages due to the existence of a strong positive link between education and firm-level productivity. More in terms of policy, this should confort those who think that the ongoing expansion of education, mainly via the massification of tertiary education is a durable source of prosperity.

At the same time, the authors find no statistically significant productivity and wage gains attached to upper secondary education (compared to workers with less than that educational attainment). The tentative conclusion is that, in the Belgian private economy, it is only at the upper end of educational distribution that productivity and wage gains materialise. The fact that wages are not affected by the possesion of a secondary degree could be interpreted as the logical consequence of Belgium's comparatively "compressed" wage structure, with relatively high sectoral minimum wages "lifting" the wage of less productive workers and aligning it on the one of their better-educated colleagues. But the no-gain result also holds for productivity. So there is probably more going on than wage compression.

One possibility is that the sample of workers with no secondary education attainment is highly positively "selected", particularly at the lower end of the educational distribution. In other works, is likely that the group of indivudals with alsmost in educational attainment that aare in employment in the Belgian private economy corresponds to the most motivated/productive part of the total corresponding population. Positive selection into employment may also occur among individuals with a higher educational atttainment, but its intensity is probably lower. If that is the case, then the productivity and wage gains attached to a degree that are presented in Chapter 6 are likely to be a lower bound (ie. they are likely to the gains that one could observe in the absence of positive selection into employment at the lower end of the educational distribution).

But there are other potential explanations to the apparent lack of gains from employing people with a secondary degree. One of them points at the key role of innovation-driven productivity growth in advanced economies like Belgium (Aghion et al., 2006). The idea is that only the most advanced forms of education (typically tertiary/university-type of degrees) contribute to the technological-, product- or managerial changes underpinning productivity growth. This perspective emphasizes the importance of increasing access and participation to tertiary education. At the same time, it could be a terrible challenge for all of those who struggle to complete secondary education. Should there be no signifciant economic gains attached to that intermiate level of educational attainment, then motivating teenagers with poor academic prospects would become intrinsically more problematic. And this would be no good news for the educators whose job consists of motivating these teenagers and prevent them from dropping out.

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