Is Part-time Employment a Boon or Bane for Firm Productivity?

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Abstract

This paper investigates the impact of various forms of part-time work on firm productivity. It is based on the estimation of labour-augmented production functions à-la Hellerstein Neumark, where the total volume of work is accomplished by three categories of workers: full-timers (the reference), long part-timers [$55- < 85\%$] and short part-timers [$< 55\%$]. The relative productivity of long- and short part-timers is estimated using a large panel of firms, covering all the sectors of the Belgian private economy, from 2002 to 2009. The main result is that employing more part-timers is detrimental to productivity. An increase of 10 percentage points of the share of total work accomplished by these workers depresses value added per hour by 1.3 % (short part-timers) to .7% (long part-timers). Interestingly, for short part-timers estimates turn positive when restricting the analysis to the retail and trade industry. The tentative conclusion is that, in Belgium, the relationship between part-time work and firm productivity is generally negative, but may depend on i) the duration of part-time jobs and ii) the industry considered.

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1 Introduction

Part-time employment has become a common feature of our economies. In Belgium, 25.1% of the total workforce consists of people working part time (Eurostat, 2012), and around 82% of firms declare employing at least one worker on a part-time basis (European Company Survey, 2009). Similar or even higher figures are observable in other European countries. Surprisingly, very little work exists about the impact of part-time work on productivity.

Economic theory provides little insight as to whether resorting to full- vs part-time jobs to accomplish a certain task is good for productivity. In most theoretical works, the number of employees (N) and their working hours (H) are perfect substitutes ($L = N \cdot H$). This assumption seems unrealistic or, at least, disputable. First, there might be a non constant relationship between hourly efficiency and the number of hours worked (Booth and Wood, 2006). And as long as part-time workers are on the rising part of that relationship, their average productivity should be higher than that of individuals who work longer hours or more days per week. Second, economists with an interest in (labour) flexibility would perhaps posit that part-time jobs help firms achieve a better match with fluctuating demand. This argument seems to be particulary relevant for the retail sector. Third, and perhaps in reference to other sectors, human capital theorists would rather predict that part-time workers are less productive; because they have accumulated less experience or are less committed than full-time employees[1]. Resorting to two or more part-time workers instead of a single full-time worker might also increase transaction/communication costs, that could cause lower productivity.

2 Related literature

The existing empirical literature on part-time work tends to overlook productivity and its importance for firms (ie. the demand side of the labour market). Many authors adopt a (labour) supply-side point of view. What they try to explain, generally using individual or household survey data, is the propensity of individuals to supply labour on a part-time basis rather than a full-time one. The theoretical background of these works essentially rests of the idea that individuals diverge in terms of preferences; and life-cycle events influence the desired degree of involvement in the labour market (Venn and Wakefield, 2005). Bardasi and Gornick (2000), for instance, show that age, education, motherhood, and the level of the spouse's income in the household are key determinants of the decision to work part-time.

Other economists focus on the part-time wage penalty and its determinants. That literature is actually a branch of the gender wage gap literature. It decomposes individual wage data using Blinder-Oaxaca methods. The latter consists of assuming that wage difference reflect i) difference in terms of productive endowment (i.e. diploma, experience but also ability) that can be explained and ii) unexplained differences i.e. discrimination. For instance, Hirsch (2004) and Booth and Wood (2006) found that differences in worker-specific skills and job-related skills (i.e. productivity endowment) accounts for much of the part-time wage disadvantage. But what is almost invariably missing from the above studies is an independent measure of productivity. Most use observable individual- or job-level characteristics that are presumed to be proxies for

[1] Several human resources specialists posit that part-time employees do not feel much obligation to contribute to the firm organization, and therefore do not engage beyond their duties and responsibilities (Katz and Kahn, 1978; Alexandrov et al., 2007; Martin and Sinclair, 2007). Accordingly, Lewis (2003) found that managers generally consider full-time workers as having higher levels of affective commitment and job dedication than have part-time staff members, where this leads to a further gap in organizational commitment and behavior (Conway and Briner, 2009).

productivity. By contrast, in this paper we use firm-level direct measures of productivity.

True enough, a small number of papers written by economists use direct measures of firm productivity. However, not all of them are satisfactory from a methodological point of view. Mabert and Showalter (1990), studying a Chicago commercial bank, find that part-time employment allows a better match of workplace operations with consumer requirements; something that ultimately leads to productivity gains. But this paper amounts to a case study, and therefore lacks generality. Arvanitis (2005), surveying Swiss firms, finds, conversely, that part-time work has a negative effect on productivity. But his identification strategy simply consists of including dummy variables to capture the presence and the intensity of part-time work. This does not qualify as causal evidence. The paper by Nelen et al. (2011) is methodologically more robust. The authors adopt the labour-augmented specification of the production pioneered by Hellerstein et al. (1999); which is probably the most suitable way of assessing the impact of labour heterogeneity (including the use of part- vs full-time jobs) on productivity. They uses a matched employer-employee data set covering Dutch pharmacies and show that pharmacies with a large share of part-time employees are more productive than firms with a large share of full-time workers. The main weakness of the paper is that the firm-level data are not longitudinal (they do not form a panel), meaning the authors cannot properly control for unobserved heterogeneity (firm fixed effects that may correlate with both productivity and part-time jobs) or short-term endogeneity causing reverse causality (e.g. productivity shocks causing changes in the importance part-time work, rather than the opposite).

The most solid paper, from a methodological point of view, is the one by Cataldi et al. (2011). It uses longitudinal (panel) firm-level survey data[2] covering most of the private sector of Belgium. The authors use state-of-the-art econometrics to control for heterogeneity and simultaneity bias. The underlying specification of the production technology is a bit ad hoc, as it does not derive from any common specification (Cobb-Douglas, CES, translog). Also the authors do not control for the amount of capital used by firms. The main results is that they find no significant impact of part-time work on productivity.

In our paper, we estimate a production function where the total volume of work is accomplished by three types of workers: those working full time, those with a long part-time work assignment and those with a short part time contract. As Cataldi et al. (2011), thus, we focus on two categories of part-time workers: short part-timers ($< 55\%$ of a full-time workload) and long part-timers ($< 85\%$) The methodology used to capture the impact of these different forms of labour is the one pioneered by Hellerstein et al. (1999).

We are in possession of a firm-level panel/longitudinal data set, covering all the sectors of the Belgian economy[3] over the period 2002-2009. The information about productivity (value added per hour) and capital come from (mandatory) financial reports compiled in Bel-first; whereas the data about the duration of work, that we use to compute the share of work accomplished part-timers vs full-times, comes for social security registers. These sources provide a measure of the effective working time (hours and days) over a trimester, and that for all the workers of the sampled firms. This represents and improvement in comparison with studies using daily or weekly measures of part-time work, and those who only analyse a (presumably representative) sample of each firm's workforce. Another strength of our results is they derive from an in-depth exploitation of the panel dimension of our data; in particular the use of econometric identification strategies that control simultaneously for i) heterogeneity bias (firm fixed effects)

[2]The Structure of Earnings and Structure of Business surveys

[3]We exclude agriculture, mining and quarrying but also the public sector and all non-profit organisations

and ii) short-term endogeneity (also known as simultaneity) bias.

As to endogeneity/simultaneity bias, following many authors in this area, we first estimate the relevant parameters of our model using "internal" instruments (i.e. lagged values of endogenous labour inputs) (IV here after). Second, we also implement the more structural approach initiated by Olley and Pakes (1996), further developed by Levinsohn and Petrin (2003) and more recently by Ackerberg et al. (2006) (ACF hereafter), which primarily consists of using intermediate inputs/materials to control for short-term simultaneity bias. Note that like Vandenberghe et al. (2011), we combine the ACF intermediate-good approach with first differences (ACF-FD), to better account for simultaneity and firm unobserved heterogeneity.

From a methodological point of view, an interesting aspect of the paper is that it shows that the results delivered by ACF-FD are completely different than those stemming from ACF alone (i.e. without FD), stressing the importance of unobserved heterogeneity in large firm-level panels.

The main result of the paper is that part-time work is detrimental for productivity defined as value-added per hour. An increase of 10 percentage-points in the share of work accomplished by long part-timers in a typical Belgian firm depresses productivity by .7%. Point estimates for short part-timers are also negative, with a 1.3% drop of productivity due to a 10 percentage-points rise in their share. Interestingly, the productivity handicap of short part-timers vanishes when reestimating the model using the (unfortunately smaller) sample of firms that report their workforce's educational attainment. Estimates for long part-timers are basically unchanged. Interestingly also, estimates turn positive (and for part-time work are even statistically significant) when the analysis is restricted to the (broadly defined) retail and trade industries. The tentative conclusion is that the relationship between part-time work and productivity is generally negative in Belgium, but may turn positive in sectors where time flexility matters a lot, e.g. to cope with a fluctuating demand. It may also depend on the duration of the part-time work. We observe indeed that long part-timers' productivity handicap is more robust to change of specification, sample perimeter or list of control variables.

The rest of the paper is organized as follows. In Section 3 our methodological choices regarding the estimation of the production are unfolded. Section 4 describes the data. Section 5 presents the econometric results, and Section 6 concludes.

3 Methodology

The methodology rests on the seminal work of Hellerstein et al. (1999), and corresponds to the one used in Vandenberghe (2011,2013) and Vandenberghe et al.(2013). In order to estimate the contribution of different categories of workers (here distinguished by the duration of their work), we consider a labour-augmented (and log-linearized) Cobb-Douglas production function linking output per unit of labour to inputs:

$$\ln\left(\frac{Y_{it}}{L_{it}}\right) = \ln A + \alpha \ln QL_{it} + \beta \ln K_{it} - \ln L_{it} \tag{1}$$

where $\frac{Y_{it}}{L_{it}}$, the productivity per labour unit in firm i at time t, is a function of the stock of capital ${K_{it}}$[4] and a labour aggregate QL_{it} reflecting labour's heterogeneity. Workers are divided

[4]We have information on firms' capital stock, which is not the case in some works (e.g. Cataldi et al. 2011).

into types k according to their characteristics (here the duration of their work). Assuming perfect substitution among all types, with different marginal products, we can specify QL_{it} as follow:

$$QL_{it} = L_{it}\mu_{i0}\left[1 + \sum_{k>0}(\lambda_{ik} - 1)P_{ikt}\right] \tag{2}$$

where $L_{it} = \sum_k L_{ikt}$ is total labour in the firm i at time t, μ_{i0} is the productivity of the reference category of workers (here full-timers), λ_{ik} is the productivity of type $k > 0$ relative to the reference and P_{ikt} is the share of type $k > 0$ workers in the firm. If we further consider workers as having the same productivity across firms, we can drop the subscript i from μ. After log transformation of QL_{it} and linearization[5], the production function becomes:

$$\ln\left(\frac{Y_{it}}{L_{it}}\right) \approx B + (\alpha - 1)\ln L_{it} + \sum_{k>0}\eta_k P_{ikt} + \beta \ln K_{it} \tag{3}$$

where $B = \ln A + \alpha \ln \mu_0$ and $\eta_k = \alpha(\lambda_k - 1)$ can be interpreted as the contribution to output of the different worker types. More precisely, the η_k coefficients reflect the percentage change in the firm's productivity when the share of category $k > 0$ workers in the plant increases of 1 unit(i.e. 100

The worker types (and the corresponding labour percentages/shares P_{ikt}) are defined as follows: S represent short part-time workers ($< 55\%$ of a full-time contract), while L represent long part-time workers ($55 \leq L < 85\%$ of a full-time contract). The contribution to the average productivity of each of these groups is estimated relative to their reference group ($F \geq 85\%$ of a full-time contract). Accordingly, the production function writes:

$$\begin{aligned}\ln\left(\frac{Y_{it}}{L_{it}}\right) = B + (\alpha - 1)\ln L_{it} + \beta \ln K_{it} + \eta^S P^S_{it} + \eta^L P^L_{it} + \\ + \gamma F_{it} + \theta_i + \omega_{it} + \sigma_{it}\end{aligned} \tag{4}$$

In eq. (4) we included a vector of controls F_{it}, which contains sector (NACE2) interacted with dummies. This vector allows to better control for systematic shocks and trends that may affect firm-level productivity along these specific dimensions. What is more, since our database does not contain price deflators, the introduction of F_{it} allows to control for the differences in inflation across sectors.

Of the error components, θ_i represents (time-invariant) unobservable firm characteristics, potentially correlated with productivity and labour inputs; ω_{it} is a short-term shock observable by the firm (but not by the econometrician) also potentially correlated with both output and (labour) inputs, while σ_{it} is a purely random term.

We estimate equations (4) with six different methods. The baseline regression [1] is an OLS estimator with robust standard errors. However, as Marshak and Andrews (1944) noticed first, the OLS estimates are likely to be biased. For example, we may think that part-time workers are over-represented in firms that are intrinsically less productive (e.g. in the service industry for instance). If this is the case, OLS coefficients would be no longer consistent. In order to cope with θ_i, we estimate a fixed effect model by resorting to first differences (FE-FD hereafter)

[5] Using the fact that $ln(1 + x) \simeq x$ if x is small.

[2], thus exploiting only within firm variations over time to estimates our coefficients, and thus eliminating the so-called heterogeneity bias.

This said, the main issue remains dealing with the (short-term) simultaneity bias ω_{it} (Griliches and Mairesse, 1995). If firms anticipate ω_{it}, when maximizing their profits, they would (partially) adjust the choice of inputs, in particular their labour inputs. For instance, an anticipated downturn could translate into a promotion of part-time contracts rather than lay-offs. If this is the case, there would exist a negative correlation between part-timers' share and productivity, leading to an underestimation of their productivity when using OLS and FE-FD coefficients.

In order to account for this simultaneity/endogeneity bias, we first use an IV strategy [3]. The latter consists of using lagged values of labour shares as internal instruments. We also implement and alternative to the IV estimation proposed by Levinsohn-Petrin (2003) (LP hereafter) [4]. The basic ingredients of LP is that $\theta_i + \omega_{it}$ can be proxied using materials/intermediate goods consumptions (e.g. electricity, purchase of services...). We also estimate the most recent development of the materials-as-proxy idea proposed by Ackerberg et al.(2006) (ACF hereafter)[5], which in essence better controls for the risk of collinearity between materials and labout input. Finally , we implement ACF in combination with FD (ACF-FE hereafter) [6] to explicitly account for the fact that the error term contains a fixed effect θ_i . This last method is our preferred one.

ACF assume that there is function $g(.)$ relating materials m_{it} to unobserved productivity :

$$m_{it} = g_t(ql_{it}, k_{it}, \theta_i + \omega_{it}) \tag{5}$$

where g_t is a strictly monotonic function, meaning that it can be inverted to deliver an expression of $\theta_i + \omega_{it}$ as a function of k_{it}, ql_{it} and m_{it}; and introduced into the production function.

Simplifying our notations to make them alike those used by ACF, productivity equation becomes[6]:

$$\ln\left(\frac{Y_{it}}{L_{it}}\right) = B + \phi ql_{it} + \beta k_{it} + \gamma F_{it} + g_t^{-1}(m_{it}, k_{it}, ql_{it}) + \sigma_{it} \tag{6}$$

where $g_t^{-1}(m_{it}, k_{it}, ql_{it}) = \theta_i + \omega_{it}$ and $\phi ql_{it} = (\alpha - 1)l_{it} + \eta_S P_{it}^S + \eta_L P_{it}^L$.

In practice, how are the parameters ϕ and β estimated?

The ACF algorithm consists of two stages. We argue that only stage one needs to be adapted to account for fixed effects. And this is done by resorting to first-differences. In stage one, like ACF, we regress productivity on composite term $\Phi_{it}(.)$ that comprises a constant, a third-order polynomial expansion in m_{it}, k_{it}, ql_{it} and our vector of controls added linearly. This leads to:

$$\ln\left(\frac{Y_{it}}{L_{it}}\right) = \Phi(m_{it}, k_{it}, l_{it}, F_{it}) + \sigma_{it} \tag{7}$$

Note that ϕ and β are clearly not identified yet, implying the need of a second stage. Note in particular that $\Phi(.)$ encompasses $g_t^{-1}(.)$ proxying $\theta_i + \omega_{it}$. The point made by ACF is that this first-stage regression delivers an unbiased estimate of the composite term $\Phi(.)$;

[6]Lower case letters indicate logarithms.

i.e. productivity net of the purely random term σ_{it}. We go a step further and also get rid of θ_i by resorting to first-differences when estimating equation (6). The resulting FD-estimated coefficients - provided they are applied to variables in levels - deliver an unbiased prediction of $\Phi(.)$. Specifically, $\Phi(.)$, net of the random term and firm-fixed effects, is calculated as $\Phi(.) = \mu_{a1}^{FD} m_{it} + \mu_{a2}^{FD} m_{it}^2 + \cdots + \mu_{b1}^{FD} k_{it} + \cdots + \mu_{c1}^{FD} ql_{it} + \cdots + \mu_{d1}^{FD} m_{it} k_{it} \ldots$, where μ_{a1}^{FD}, μ_{a2}^{FD}, ... represent the (first differences) estimated coefficients of the third-order polynomial expansion.

As an aside, also note the presence in Φ_{it} of a third-order terms in (inter alia) ql_{it} and its components, namely l_{it}, P_{it}^S and P_{it}^L. To this point, the production function (a Cobb-Douglas) has been specified so that workers of different types have different productivities but are perfectly substitutable. Because this specification may be too restrictive, we should also consider evidence from estimates of a production function in which worker types (between themselves and with capital) are imperfect rather than perfect substitutes. Resorting to a translog specification is what Hellerstein and al. (1999) did in their seminal paper. But the ACF first stage equation above consists of regressing the log of productivity on a third-order polynomial that contains interaction terms between the various labour inputs and capital. When we report ACF and FD-ACF estimates below, one should thus bear in mind that we have gone part-way toward doing what Hellerstein and al. (1999) do when estimating a translog production function to allow for imperfect substitutability.

Returning to ACF, we basically argue that their second stage is unaffected by the stage-one modification we have introduced. The predicted value $\hat{\Phi}_{it}$ and candidates values for the coefficients ϕ, β and γ[7] are now used to model the unobserved productivity:

$$\hat{\omega}_{it} = \hat{\Phi}_{it} - \hat{\phi} ql_{it} - \hat{\beta} k_{it} - \hat{\gamma} F_{it} \tag{8}$$

Further, ACF assume that productivity follows a first-order Markov process:

$$\omega_{it} = E(\omega_{it}|\omega_{it-1}) + \psi_{it} = g(\omega_{it-1}) + \psi_{it} \tag{9}$$

Where ψ_{it} represents the innovation in productivity. By regressing non-parametrically[8] (implied) ω_{it} on (implied) ω_{it-1} , ω_{it-2}... , one gets residuals that correspond to the (implied) ψ_{it} that can form a sample analogue of the orthogonality (or moment) conditions identifying ϕ, β and γ.

We would also argue that residuals ψ_{it} are orthogonal to our controls F_{it}.

Like ACF, we would also argue that capital in period t was decided at period $t-1$ (or earlier). The economics behind this is that it may take a full period for new capital to be ordered and put to use. Since k_{it} is actually decided upon $t-1$, $t-2$, ..., it must be uncorrelated with the implied innovation terms ψ_{it}:

$$E\left[\psi_{it}|k_{it}\right] = 0$$

Firms decide on the amount of materials in t, whereas labour inputs observed in t are chosen sometime before, although after capital k_{it}; say in $t-b$, with $0 < b < 1$. The justification for this is that it may take some time before employment adjustment decisions get effectively

[7]OLS estimates.
[8]using fourth-degree polynomial approximation

implemented, particularly in the presence of high employment protection as it is the case in Belgium (Ornaghi and Van Beveren, 2011). The consequence is that ql_{it} will be correlated with at least part of the productivity innovation ψ_{it}. On the other hand, assuming lagged labour inputs were chosen at time $t-b-1$ (or earlier), ql_{it-1}..., should be uncorrelated with the innovation terms ψ_{it}. This gives us the third (vector) of moment conditions needed for identification of $\hat{\gamma}$:

$$E\left[\psi_{it}|ql_{it-1}\right] = 0$$

4 Data

For our empirical estimation, we merged two data sets covering the period 2002-2009. On the one hand, the Bel-first database contains firm-level financial information for all sectors forming the Belgian private economy. Firms are largely documented in terms of industry classification, size, capital, materials used[9] and value added. Descriptive statistics are to be found in Table 1.

On the other hand, via the Carrefour data warehouse (that compiles social security records), using firm identifiers, we have been able to inject information on the duration of work of all workers employed by the above firms.

Table 1: Descriptive statistics, main variables

	Value added per hour[log]	N. of empl. [log, weighted]	Capital[log]	Short part-time [share,*]	Long part-time [share,*]
2002	-3.256	3.253	7.060	0.055	0.127
2003	-3.217	3.298	7.139	0.049	0.101
2004	-3.181	3.315	7.208	0.048	0.106
2005	-3.150	3.345	7.311	0.047	0.108
2006	-3.114	3.385	7.442	0.047	0.109
2007	-3.072	3.414	7.541	0.045	0.109
2008	-3.067	3.441	7.614	0.044	0.113
2009	-3.072	3.428	7.650	0.047	0.141
N. of obs.	25,913				

*: weighted Source: Belfirst-Carrefour

Of central importance in this paper is the definition and the measurement of part-time work. In the Belgian labour law, part-time work is defined as work done on a regular and voluntarily basis, for a shorter period than the normal working time (38h/week). A part-time job should in principle consist of minimum 1/3 of a full-time assignment[10]. Yet, this threshold can be renegotiated at the sector and firm/plant level. Part-time work tends to be a right granted by the legislator to individual workers. There are of course regulations reflecting employers' priorities[11].

Successive governments have passed laws to increase the flexibility of working time, mainly with the aim of helping workers combining their career with their family life. In 2002 (which coincidentally is the first year of hour panel) the "time credit" system was enacted. That scheme

[9] Or intermediate goods (Table 2, column 1) defined as the value of goods and services consumed or used up as inputs in production by firms, including raw materials, services and other operating expenses.

[10] And the work should be done in blocks of at least 3 consecutive hours, although some exceptions apply. The public sector has its own arrangements that may diverge slightly.

[11] For example, the right to work part-time is much more limited inside small firms (<10 employees), and it cannot be claimed by more than to 5% of all employees at a time.

offers workers for the private sector the possibility to temporarily interrupt their career for some some months, or reduce working hours with one-half or one-fifth.

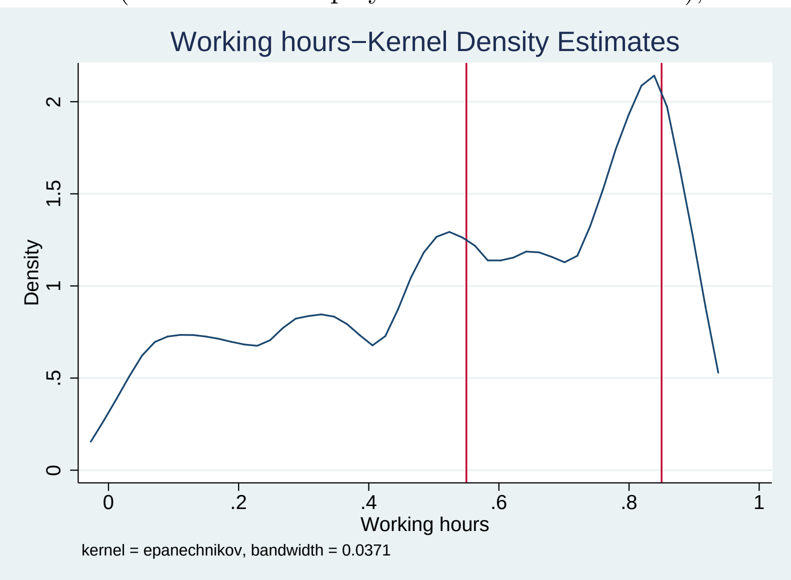
We find traces of these two fractions in our data (Figure 1). Social security registers from which they derive contain, for each worker, in each firm located in Belgium, the information on the fraction of the full-time equivalent(FTE) worked by workers, on a trimestrial basis. That percentage combines the number of hours per day or week (the traditional way of measuring part-time work) with the number of days worked over the trimester[12]. Figure 1 shows the density plot for all cases where the fraction is < 1. It is immediate to see that the distribution displays two peaks: around 50% and 80%. These echo the above-mentioned distinctive features of the Belgian legislation on part-time employment.

The HN methodology used in this paper imposes using a limited number of labour categories. At the same time, it would be inadequate to pool all part-timers into one single category. Anecdotal evidence, but also the existing literature, suggest that the nature of part-time work varies a lot with its duration (Tilly 1991, Russo and Hassink 2008, Martin and Sinclair 2007). Our choice is similar to that of Cataldi et al. (2012). We built three labour shares and use the first two to estimate our HN equation ;

i) short part-timers, whose effective workload is lower than 55% of a full-time contract (FTE< 0.55); ii) long part-timers whose effective workload is between 55% and 85% of a full-time contract ($0.55\leq$ FTE < 0.85); iii) full-time workers, the reference category, whose workload is 85% or more than a full-time contract (FTE ≥ 0.85) (see Table 2 for descriptive statistics).

Note that the first category includes the 50% threshold visible in Figure 1, whereas the second category encompasses the 80% threshold.

Figure 1: Distribution of part-time employment in the Belgian private economy according to duration (1= full-time employment over the trimester), 1998-2006, Kernel density estimates



*Notes:*the red vertical lines correspond to the .55 and .85 thresholds used here do distinguish short part-timers, long-part-timers and full-timers

[12]Although it varies a bit from industry to industry a full-time trimestrial workload consists of 7.6 hours/day on average, over a 65-67 days.

All worker-level measures have been aggregated at the firm-level, and each variable has been weighted to take into account of the effective duration of work over the trimester[13]. Table 1 shows that between 10 and 14% of total hours are accomplished by long part-timers. The share by short part-timers is much smaller at about 5%.

Our econometric models systematically include a vector of control variables F_{it}. The latter comprise year/sector interaction dummies. F_{it} also comprises the (weighted) share of female workers. Not surprisingly, women are over-represented in part-time jobs, almost $70,5\%$ of part-time workers are female, while women represent only $21,9\%$ of the full-time workers. We also add a measure of the average age of the workforce and of age dispersion inside each firm (Table 2). Both the degree of feminisation and the age structure are potential determinants of productivity (van Ours et al. 2010, Vandenberghe 2011, 2013, Vandenberghe et al. 2013). And they can simultaneously be correlated with the importance of part-time work (D'Addio et al 2010, Manning and Petrongolo 2008). Therefore, it seems reasonable to control for these two factors when studying the causal relationship between working-hours and productivity.

Additionally, F_{it} contains the (weighted) share of blue-collar workers (ref= white-collar workers). In Belgium, the blue- vs. white-collar distinction essentially reflects the type of employment contracts applicable . We propose to use it here as a proxy for education and skills[14], that we do not observe in our data, but which may be correlated with both productivity and duration of work, causing bias. There is indeed evidence that white collars are over-represented among long part-time employees.

Table 2: Descriptive statistics, Control variables

	Interm. goods [log]	Female [share*]	Age [mean*]	Age [std*]	Blue-collar [share*]
2002	8.360	0.265	37.034	8.625	0.483
2003	8.474	0.267	37.364	8.780	0.486
2004	8.574	0.269	37.731	8.823	0.489
2005	8.701	0.269	38.038	8.853	0.492
2006	8.858	0.269	38.296	8.898	0.496
2007	8.943	0.266	38.623	9.037	0.496
2008	9.030	0.268	38.917	9.154	0.498
2009	8.934	0.269	39.364	9.148	0.508
N. of obs.	25,913				

* weighted Source: Belfirst-Carrefour

Bel-first contains a direct measure of educational attainment. That information a priori constitutes a better control than the above-mentioned variables. Unfortunately is only available for a subsample of firms. We therefore decided to used it only to carry out robustness checks.

Finally, note that some standard filters have been applied to the original data set. We dropped the "Agriculture" and "Mining and Quarrying" sectors. These two sectors represent together less than 1% (37 firms) of the whole sample. Accounting for the missings, this ulti-

[13]Shares of part-timers consists, for each year by firm observation, of the ratio of i) the (weighted) number of workers belonging to a category to ii) the (weighted) total of workers in the firm; where weights are the trimestrial fraction of a full-time equivalent job

[14]In truth, the correspondence blue-collar = manual work performed by individuals with little education, versus white-collar contracts = intellectual work performed by individuals more educated suffers more and more exceptions.

mately lead to and unbalanced panel of around 3,800 firms, for a total of 25,826 observations, representing ten sectors/industries at the NACE two-digit level (see Appendix I for details).

5 Econometric results

5.1 Main results

Table 3 represents the parameter estimates delivered by OLS, FE-FD, LP and IV methods, whereas Table 4 contains the results from the ACF and ACF-FE estimations, and also those of robustness analysis. Remember that the ACF-FE is our preferred model as it is the only one that controls simultaneously for i) heterogeneity (FE) and ii) simultaneity biases. All the standard error estimates reported in Tables 3 and 4 are robust to firm-level clustering.

Table 3: Parameter estimates (SE): OLS, FE-FD, LP and IV methods

	(1) OLS	(2) FE-FD	(3) LP	(4) IV
Short part-time (η^S)	-0.292***	-0.185***	-0.454**	-0.376***
	(-7.91)	(-4.84)	(-3.07)	(-3.54)
Long part-time (η^L)	-0.315***	-0.105***	-0.384***	-0.293***
	(-13.01)	(-5.55)	(-4.25)	(-5.81)
N. of obs	25,826	22,060	11,903	22,340
Controls	Share women, share blue-collar, mean age, std age	Share women, share blue-collar, firm FE mean age, std age	Share women, share blue-collar, mean age, std age	Share women, share blue-collar, mean age, std age

Source: Bel-first & Carrefour database; Std errors are robust to firm-level clustering: t statistics in parentheses.
η^S: contribution to value added of part-time employees who work less than 55% of a FTE;
η^L: contribution to value added of part-time employees who work between 55% and 85% of a FTE.
* ($p < 0.1$), ** ($p < 0.05$), *** ($p < 0.001$)

All OLS, FE-FD, LP and IV results (Table 3) suggest that both short- and long part-timers are significantly less productive than full-timers. OLS shows that a 10 percentage-point increase in the share of short (long) part-time workers leads to a productivity decrease of about -2.9% (-3.2%). Yet, OLS estimates are known for being particularly poor at delivering causal evidence.

To control for firm-level unobserved heterogeneity, we first implement FE-FD, where parameters are estimated using only within-firm variation. Results point at a lower productivity handicap between part-timers and full-time workers: a ten percentage-point rise of the share of short (long) part-time workers depresses average productivity by -1.9% (-1.1%). The significant drop in point estimates when controlling for firm fixed effects validates the idea that there is (self)segregation of part-timers between firms and sectors. Part-time workers are over-represented in firms/sectors that are intrinsically less productive. This result accords with previous findings (Meulders and Plasman 1993; OECD 1994; Smith et al. 1998 and O'Dorchai et al. 2007 for Belgium).

Nonetheless, FE-FD still suffers from simultaneity bias. The latter bias can be controlled via LP and IV methods; though unfortunately not in conjunction with the heterogeneity bias.

If anything, our LP estimates point at larger productivity handicap than OLS: from -4.5% for short part-time workers, to -3.8% for long part-time workers; while IV estimates, where labour inputs are instrumented using their 1 to 4 lags, are very similar to the OLS ones.

Table 4 contains the results obtained when implementing the ACF idea. The first column reports the results of the ACF strategy as such (without firm fixed effects). They suggest a productivity handicap that is somewhat intermediate between the LP and the OLS estimates. A ten percentage-point increment of the share of short (long) part-time work translates into a -4.7% (-1.6%) drop of productivity per hour. This is in part coherent with the findings of previous papers applying the ACF method (see Eberhardt and Helmers (2010), Vandenberghe et al.2011). Indeed, as explained above, without fixed effects, ACF estimates tend to be biased toward OLS.

The rest of Table 4 contains our preferred results (ACF-FD); those that stem from a method that combines FD and the materials-as-proxy idea. Results show that a ten percentage-point increase for the share of short (long) part-timers causes a productivity drop of -1.3% (-0.7%). These estimates are lower in magnitude than all those obtained so far. But are they nonetheless statistically significant. And they lead to the main conclusion of this paper which is that, in the Belgian context, the relationship between part-time work and firm productivity is generally negative.

Finally, as an aside, remember that ACF (and ACF-FE) results, due to the inclusion of interaction terms between the various labour share variables, is a way to allow for imperfect substitutability across labour types (Hellerstein and al., 1999). We interpret the similarity between our ACF-FE results and those of the FE-FD production function as a possible indication that the assumption of perfect substitutability may not be abusive, and be a major source of distortion of the key estimates.

5.2 Robustness Analysis

In order to assess the robustness of our ACF-FD results, we have undertaken two further steps in our analysis. First, we reestimate our preferred model (ACF-FD) using the (smaller) sample of firms for which we possess information on the educational attainment of the workforce. The latter consists of a breakdown of the total labour[15] into workers with i) a primary education attainment (ref.), ii) a secondary education attainment, iii) a 2-year college/bachelor attainment and, iv) those with a university/master attainment. We add that information to the list of controls in F_{it}. The interest of doing so is that we better control for the fact that our work duration categories may consist of individuals who differ significantly in terms of educational attainment. As has been amply shown in the litterature, education is a key determinant of individual but also firm-level labour productivity (Vandenberghe and Lebedinski, 2013). The share of blue-collar workers for which we control everywhere else may, in the Belgian context, be a proxy for low educational attainment. Still, many would rightly argue this is insufficient to properly control for the fact that part-time employees could be less educated, and thus intrinsically less productive.

The results (Table 4)contain evidence that it might be the case, but mainly for short part-timers. The productivity estimate for them is still negative: a 10 percentage point increase in the share of short part-time workers lead to -0.35% decrease in productivity). But it is no longer statistically significant. Conversely, point estimates for long part-timers are basically unchanged

[15]Measured at firm level in full-time equivalent

when education is accounted for: these workers still appear significantly less productive than full-timers.

Table 4: Parameter estimates (SE): ACF methods, including robustness analysis

	(1) ACF	(2) ACF_FE	(3) ACF_FE[a]	(4) ACF_FE[b]
Short part-time (η^S)	-0.472***	-0.131*	-0.0352	0.360*
	(-4.01)	(-1.75)	(-0.18)	(1.77)
Long part-time (η^L)	-0.156***	-0.0711***	-0.0810**	-0.0126
	(-4.66)	(-4.64)	(-2.62)	(-0.23)
N. of obs.	18,415	18,415	10,582	6,251
Controls	Share women, share blue-collar, mean age, std age	Share women, share blue-collar, firm FE mean age, std age	Share women, shares education attainment mean age, std age	Share women, share blue-collar, mean age, std age

Source: Bel-first & Carrefour database; Std errors are robust to firm-level clustering: t statistics in parentheses.
[a]: We use a (smaller) sample of firms for which we possess information on the educational attainment of the workforce: (shares of workers having a secondary, a two years/bachelor, a master attainment).
[b]: We use a sub-sample including only the sectors "Wholesale trade" (NACE 41), "Retail trade" (44,45), "Real Estate and Rental and Leasing" (53), "Arts, Entertainment, and Recreation" (71), "Accomodation and food" (72).
η^S: contribution to value added of part-time employees who work less than 55% of a FTE;
η^L: contribution to value added of part-time employees who work between 55% and 85% of a FTE.
* ($p < 0.1$), ** ($p < 0.05$), *** ($p < 0.001$)

Second, we focus on the sectors forming the (broadly defined) retail and trade industry, namely "Wholesale trade" (NACE 41), "Retail trade" (44,45), "Real Estate and Rental and Leasing"(53), "Arts, Entertainment, and Recreation" (71),"Accomodation and food" (72). This industry has a higher incidence of part-time jobs. More importantly, it includes activities where, a priori, part-time work is conducive to greater flexibility, and may help firms achieve a better match with the fluctuating demand; something that should ultimately translate into a higher productivity per hour. We find evidence that this might be true (Table 4, last column). When focusing on the retail/trade/food and accommodation industries, point estimates turn positive, and for short part-time work are even statistically significant. A 10 percentage point percent rise in the share of short part-time workers leads to a 3.6% surge in hourly productivity. The estimate for long part-time is not statistically different from zero. The tentative conclusion is that productivity also depends on the duration of the part-time work (short part-time is not equivalent to long part-time) and on the sector of activity.

6 Conclusion

Part-time employment has steadily grown over the past two decades as a response to major socioeconomic changes. In Belgium, like in many other OECD countries, governments have passed laws to increase the flexibility of working time. In Belgium, as our data confirms, the dominant form of part-time work corresponds to long part-time work. This reflects the popularity of the so-called "four fifth" schedules (ie. the right to work 80% of the reference full-time duration). The prime aim of that scheme is to help workers combine their career with their family life. By enacting such a right, the legislator has essentially responded to a request made by the workers (and their unions). These represent the supply side of the labour market.

An open question is whether long part-time work, but also the less frequent short part-time work, is a good thing for firms who represent the demand side of the labour market.

It is quite surprising, in the light of the numerous questions raised by part-time work, that solid evidence on its impact on firms' performance remains scarce. Economic theory is of little help to formulate solid predictions, and existing empirical estimations remain inconclusive. The aim of this paper is to fill that relative void. It is based on the in-depth analysis of firm-level panel data covering the Belgian private sector, and provides clausal evidence as to how part-timers effect productivity. It has the advantage of distinguishing short and long part-timers, and recurring to state-of-the-art econometric analysis.

The main result of the paper is that part-time work is generally detrimental for productivity defined as value-added per hour. In a typical private (and for-profit) firm located in Belgium, an increase of 10 percentage points in the share of total work accomplished by short(long) part-timers depresses productivity by 1.3% (.7%). Interestingly, the productivity handicap of short part-timers tends to vanish when explicitly controlling for educational attainment. Interestingly also, the handicap becomes an advantage when restricting the analysis to retail and trade. Both econometric shifts make economic sense. Short part-timers are less educated than full-timers, and retail and trade are sectors where time flexibility is crucial to maximise efficiency. The results for the (more numerous) long part-timers are qualitatively different. Almost all our econometric results show that they are less productive, even if the overall magnitude of their handicap is not large. Explicitly controlling for education does not lower estimates of their handicap (which incidentally suggests that they are much alike full-timers in terms of educational attainment). Unlike short part-timers, they do not generate productivity gains in the retail and trade industry. In short, our results suggest that short and long part-timers diverge in terms of education and, most importantly, occupations. Long part-timers seem to be active in industries and/or occupations where the additional degree of job-related experience, or simply of job presence characterizing full-timers, matters for productivity.

7 References

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8 Appendix

Table 5: Sectors/industries and NACE2 codes/definitions

NACE2 code	Industry
22	'Utilities'
23	'Construction'
31-33	'Manufacturing'
42	'Wholesale Trade'
44-45	'Retail Trade'
48-49	'Transportation and Warehousing'
51	'Information'
52	'Finance and Insurance'
53	'Real Estate and Rental and Leasing'
54	'Professional, Scientific, and Technical Services'
55	'Management of Companies and Enterprises'
56	'Administrative and Support and Waste Management and Remediation Services'
61	'Educational Services'
62	'Health Care and Social Assistance'
71	'Arts, Entertainment, and Recreation'
72	'Accommodation and Food Services'
81	'Other Services (except Public Administration)'