The Impact of Part-Time Work on Firm Total Factor Productivity: Evidence from Italy

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Abstract

In this paper we explore the impact of part-time work on firm productivity. Using a large panel dataset on all corporations in Italy for the period 2000-2010, we first recover an estimate of the total factor productivity (TFP) of each firm for each year. We use different approaches aimed at solving the simultaneity issue. In particular, we develop a version of the control function method proposed by Ackerberg et al. [2006] that allows to also take into account firm-specific fixed-effects (ACF-FE). We then match TFP estimates with the information deriving from a uniquely rich firm-level survey conducted in Italy (RIL) and estimate the impact of part-time work on TFP. We find that an increase of one standard deviation in the part-time share (0.14) reduces TFP by 2.03%. The results suggest that this harmful effect is carried out by horizontal rather than vertical part-time arrangements. We also find that firms declaring to use part-time work in order to accommodate for workers' requests suffer the most from part-time. Moreover, we show that the so called 'flexible' and 'elastic' clauses are successful in reducing the negative impact associated with part-time.

Keywords: Part-time work; Horizontal, vertical and mixed part-time contracts; Flexible and elastic clauses; Firm total factor productivity (TFP); Semiparametric estimation methods; ACF-FE.
JEL codes: L23; L25; J23.

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1 Introduction

In this paper, we investigate the impact of part-time work on firm productivity.

Since the mid-1970s, part-time work has been increasingly used and now represents a pervasive feature of work arrangements. According to Eurostat, about one fifth of the total employees in Europe was working on a part-time basis in 2010 and about 67% of European firms had at least one part-time employee in 2008.

In view of the widespread diffusion of part-time work, the issue whether it is beneficial or not for firm productivity is of great relevance, for both managers and policymakers. Nonetheless, only a limited number of studies addressed it, while the bulk of the literature on part-time has been focused on the supply side, also in the perspective of its alleged positive role in increasing female participation to the labor market.

To our knowledge, only three papers try to empirically assess the impact of part-time work on (labor) productivity. Garnero et al. [2014], using a longitudinal matched employer-employee dataset on Belgian private sector firms for the period 1999-2010, find that part-time workers are relatively more productive than full-time ones and that this effect is essentially driven by male long part-timers. On the contrary, Specchia and Vandenberghe [2013], for a large panel of firms covering all the sectors of the Belgian private economy over the period 2002-2009, find that part-time workers are relatively less productive with respect to their full-time counterparts. According to their estimates, an increase of 10 percentage points in the share of total work accomplished by part-timers, lowers the average labor productivity (defined as value added per hour) by 1.3%, for short part-timers, and 0.7%, for long part-timers. Künn-Nelen et al. [2013], focusing on the Dutch pharmacy sector for the year 2007, find that part-timers are relatively more productive that full-timers. A 10% increase in the part-time share is associated with 4.8% higher labor productivity. Hence, the literature on this topic is inconclusive: only two countries have been examined (Belgium and the Netherlands); using similar panel data for the same country, Garnero et al. [2014] and Specchia and Vandenberghe [2013] find contrasting results; while Künn-Nelen et al. [2013] focus on a very detailed sector.

The theoretical literature has highlighted several channels through which part-time work may affect firms both with respect to the individual productivity of labor, i.e. the labor productivity of part-timers with respect to full-timers, and with respect to the productivity of the firm as a whole, i.e. the total factor productivity.

If there exists a non-constant relationship between labor productivity and the number of hours worked, the average labor productivity of part-timers and full-timers will differ (Barzel [1973]). Pierce and Newstrom [1983] argue that part-timers are more productive than full-timers because part-time work relieves them from the stress associated with longer working time, while Barzel [1973] suggests that part-timers are less productive than full-timers because the working day is characterized by start-up costs. Moreover, according to the human capital theory, part-timers are less productive than full-timers because they have lower incentives to invest in their accumulation of human capital.

Besides affecting labor productivity, the use of part-time work may also influence firm productivity at the establishment level. On the one hand, employing two workers on a part-time basis rather than one full-time worker, leaves room for communication and coordination costs and, consequently, can reduce firm productivity (Lewis [2003]). On the other hand, organizational issues may lead part-time work to be beneficial for firm productivity: firms whose activities are concentrated in only few hours per day or firms whose operating hours exceed the full-time working week may benefit from part-time work arrangements (Owen [1978]).

It is better to clarify that, differently from Garnero et al. [2014], Specchia and Vandenberghe [2013] and Künn-Nelen et al. [2013], who interpret their findings in terms of labor productivity differentials (in their empirical specifications, results can be interpreted according to both dimensions), here we explicitly focus on the impact of part-time work on firm total factor productivity (TFP). Indeed, we believe that the bulk of the effect of part-time work has to do with organizational efficiency, which is captured by TFP.

In practice, in our empirical analysis, we proceed into two steps. From the first step we recover estimates of the TFP, our measure of firm productivity, defined as the residual of a (log transformed) Cobb-Douglas production function. We take care of endogeneity issues involving the estimation of production functions using a modified version (similar to that proposed by Vandenberghe et al. [2013]) of the semiparametric approach developed by Ackerberg et al. [2006], that explicitly takes into account firm-specific fixed-effects. In order to recover precise TFP estimates, we exploit the large size of AIDA, a dataset provided by the Bureau Van Dijk collecting balance sheet information for (almost) all the private sector Italian corporations for the period 2000-2010. We then assess the impact of part-time on TFP using a uniquely rich and partially-panel firm-level survey (RIL) conducted in Italy by ISFOL[1] in 2005, 2007 and 2010. The firm tax number (*codice fiscale*) enables us to match the TFP estimates obtained from the AIDA dataset with the RIL dataset.

The main result is that part-time work is detrimental to firm productivity: one standard deviation increase in the part-time share (0.14) is estimated to decrease TFP by 2.03%. We interpret this finding in terms of communication and transaction costs that part-time

[1] ISFOL is the 'Institute for the Development of Vocational Training for Workers' and is part of the Italian Ministry of Labor and Social Policy.

imposes on the firm, consequently lowering its general efficiency.

Thanks to the rich information on part-time work provided by the RIL dataset, we are able to investigate some of its dimensions which, at least to our knowledge, have never been explored so far. In particular, we are able to distinguish between three types of part-time work: horizontal, vertical and mixed. Horizontal part-time, the most common, involves a reduction of the *daily* working time (e.g. working every working day 5 hours per day, instead of 8 hours per day as full-timers generally do). Vertical part-time, on the contrary, involves a reduction of the number of working days with respect to full-timers (e.g. working 8 hours per day, but only on Monday, Tuesday and Wednesday), while mixed part-time combines horizontal and vertical characteristics. Our findings suggest that the negative effect of part-time is carried out by the horizontal (and mixed) part-time, whereas the vertical part-time is found to have virtually no effect on firm productivity. Moreover, we have information on whether part-time is used in order to accommodate for the worker's request of a part-time contract or, alternatively, because it satisfies firms' needs (e.g. because it is believed that part-time work better suits the production process). Our results show that part-time has a stronger (negative) impact when the firm uses it to accommodate for workers' requests. Still, we find that also this last category of firm suffers from part-time. Finally, we have information on whether the firm uses part-time jointly with the so called 'flexible' (for horizontal part-time) and/or 'elastic' (for vertical part-time) clauses, instruments intended to increase the flexibility in the use of part-time work for the employer. We find evidence that clauses make part-time less harmful, thus concluding that clauses may represent a good compromise between firms and workers' needs and may eventually lead more firms to hire on a part-time basis workers who ask for it.

The rest of the paper is structured as follows: in Section 2 we go through a literature review; in Section 3 we discuss the empirical model and the identification strategy; Section 4 provides a description of the Italian situation; Section 5 describes the datasets used in the analysis; Section 6 shows and discusses our results; Section 7 concludes.

2 Literature Review

The academic literature on part-time work has been traditionally concerned with the supply side of the market. Using individual level data, it has been alternatively focused on investigating issues such as the determinants of part-time labor supply, its role for granting individuals (especially women) a satisfactory work-life balance or the part-time *versus* full-time wage gap.[2]

When dealing with the demand side, both the theoretical and the empirical literature on part-time work has been more concerned with the determinants of part-time demand, rather than on the its role in affecting firm productivity (see Montgomery [1988]).

Nonetheless, the theoretical literature has proposed several theories on how the use of part-time work would affect productivity. In general, it is possible to distinguish among two macro categories: theories which concentrate on the impact of part-time on individual productivity of labor and theories emphasizing the impact of part-time on the firm organizational efficiency.

The work by Barzel [1973] represents the starting point of the first set of theories. Whether part-timers are more or less productive than full-timers in the hours they work depends on the relationship between labor productivity and the number of hours worked during the day. If labor productivity is constant across the hours of work, part-timers and full-timers have the same level of average labor productivity. When this constant relationship breaks down, there is room for productivity differentials between them. Depending on the nature of such a relationship (e.g. positive sloped curve or inverted U-shaped curve) part-timers may be more or less productive than full-timers. Barzel [1973], emphasizing the presence of start-up costs, according to which labor productivity is lower during the first hours of work for picking up only slowly during the day, argues that part-time workers have a lower average productivity than their full-time colleagues, essentially because part-timers stop working before full-timers. On the contrary, if one is willing to believe that labor productivity increases during the working day up to some point after which it starts decreasing, it turns out that the average labor productivity of full-timers may be lower than that of part-timers. This is the point made by Brewster et al. [1994], who argue how long working hours, causing stress and tiredness, can make full-timers less productive than part-timers. Resorting to the human capital theory initiated by Becker [1964], another strand of the literature suggests that part-timers have less incentives in investing in (firm-specific) human capital. This lack of incentives, coupled with the fact that part-timers are in general less committed to career goals than their full-time colleagues (Martin and Sinclair [2007]), makes them less involved in training activities and eventually results in lower productivity levels (Nelen and De Grip [2009]).

The second set of theories emphasizes the role of part-time work in affecting the productivity of the firm as a whole, rather than the individual labor productivity. Several channels

[2] See, for example: Blank [1979], for an assessment of the role of part-time work in labor market transitions of women; Ermisch and Wright [1993], for a discussion on part-time *versus* full-time wage gaps of British women and on the determinats of their decision to work part-time; Gregory and Connolly [2008], for an assessment of the role of part-time in granting work-life balance for women.

for this effect are proposed, which lead to contrasting results. On the one hand, Lewis [2003] argues that part-time work may give rise to coordination costs, which eventually decrease the productivity of the firm. While the potential for these costs is lower in jobs where workers can be easily substituted for each other (e.g. along the assembly line), it could be relevant for jobs where task-specific skills matter (e.g. clerical work). In this case, part-time work may as well create information inefficiencies and communication costs. Edwards and Robinson [2000] also highlight how part-time labor may damage firm productivity because of managers' prejudices towards part-timers: managers would think that part-timers are not committed workers. This belief would lead them to underuse part-time workers, hence causing the firm to suffer productivity losses. On the other hand, papers related to the demand of part-time labor (e.g. Owen [1978]), have emphasized the allocation efficiencies that part-time may produce. In particular, firms experiencing workload peaks in certain hours or days and firms whose operating hours exceed the full-time working hours may benefit from part-time work. Since these conditions are likely to be found in the service industry (and, especially, in the retail industry), most of the potential benefits of part-time work are to be expected for that kind of firms. Owen [1978] also suggests that part-time work may represent a valid option when the demand facing the firm is characterized by fluctuations such that an additional full-time worker may be 'too much', while an additional part-time worker may be 'good enough'.

In conclusion, whether the overall effect of part-time work on both labor and firm productivity is positive or negative is not clear and is presumably the result of the interplay of many contrasting forces.

The empirical literature on the impact of part-time on firm productivity is scarce and the emphasis has been put, with no exceptions, on labor productivity differentials.

A strand of the literature, using individual-level data, investigates labor productivity differentials between part-timers and full-timers by considering differences in hourly wages, finding contrasting results. For example, Ermisch and Wright [1993], for British women, and Baffoe-Bonnie [2004], for USA, find significant wage differential between part-timers and full-timers, with part-timers being paid less; whereas, Hirsch [2005], after controlling for individual and job characteristics, find no significant wage gap in his USA sample. However, these results are valid (obviously: in relation to assessing the existence of productivity differentials) to the extent in which hourly wages reflect labor productivity.

Using firm-level data, Arvanitis [2005] is the first to assess the relationship between part-time and a direct measure of labor productivity (defined as sales per employee) through a reduced-form equation relating labor productivity to firm's characteristics. Though simply constructing a dummy variable indicating whether the firm uses part-time, he finds, for a sample of Swiss firms, that part-time labor is negatively related to labor productivity.

Beside Arvanitis [2005], there are three papers assessing labor productivity differentials between part-timers and full-timers through the use of a direct measure of labor productivity, i.e. using firm-level data, and in the context of production functions.

On the one hand, Garnero et al. [2014] use a large matched employer-employee dataset for Belgium for the period 1999-2010 with the aim of exploring the relationship between wage/productivity differentials between part-timers and full-timers, for evaluating whether there are some employer rents associated with the use of part-time. For what concerns productivity differentials, they find that part-time employees are significantly more productive than their full-time colleagues. In particular, they show that this result is essentially driven by male long[3] part-timers, whereas the other categories, i.e. female long and short part-timers and male short part-timers, do not exhibit significantly different labor productivity with respect to the reference group (i.e. full-time males). Their empirical model is based on the separate SYSTEM-GMM[4] estimation of a labor productivity function (following the method proposed by Hellerstein et al. [1999]) and a wage function at the firm level. The estimated contribution of different categories of workers (e.g. full- *versus* part-timers) to average labor productivity and to average wage, allows to investigate whether some of them are sources of rents for the employer.

On the other hand, Specchia and Vandenberghe [2013], sticking to the framework proposed by Hellerstein et al. [1999], again for Belgium (though for a different dataset with respect to the one used by Garnero et al. [2014]), find that part-timer are in general less productive than full-timers. In particular, this negative effect is found to be bigger for short part-timers than for long part-timers.[5] According to their most robust estimates, using the procedure proposed by Vandenberghe et al. [2013], a 10 percentage point increase in the part-time share causes the average labor productivity to decrease by 1.3%, for short part-timers, and by 0.7%, for long part-timers. They also find that the coefficient associated to the short part-timers turns positive in the retail industry, meaning that their relative productivity is higher than that of their full-time colleagues.

Finally, Künn-Nelen et al. [2013] focus on a cross-sectional dataset for the Dutch pharmacy sector. Again resorting to the method proposed by Hellerstein et al. [1999], they find that part-timers are more productive than full-timers. According to their estimates, a 10% increase in the part-time share is associated with an increase in the average labor

[3]Garnero et al. [2014] define 'long' part-timers as those working more than 25 hours per week.

[4]'SYSTEM-GMM' is the usual way in which the literature refers to the estimator proposed by Arellano and Bover [1995] and Blundell and Bond [2000].

[5]Specchia and Vandenberghe [2013] define 'short' part-timers as those whose working time is less than 55% with respect to that of full-timers and 'long' part-timers if it is between 55% and 85%.

productivity by 4.8%.

Since the paper by Künn-Nelen et al. [2013] is concentrated on a very particular industry, our paper ends up being comparable with Garnero et al. [2014] and Specchia and Vandenberghe [2013], who, though analyzing the same country in (almost) the same years, obtain contrasting results. The fact that they interpret their results in terms of labor productivity differentials does not prevent us from a direct comparison. The coefficient associated to part-time work in their empirical specifications can be alternately interpreted in terms of labor productivity differentials and in terms of impact on TFP.

3 Empirical Model and Identification

In order to investigate the relationship between part-time work and firm productivity, we consider the following production function:

$$Y_{it} = f(A_{it}, L_{it}, K_{it}) \tag{1}$$

where output (Y_{it}) is modeled as a function of labor (L_{it}), capital (K_{it}) and TFP (A_{it}). If, on the one hand, we observe (a measure of) output, labor and capital, on the other hand, TFP is unobserved. Ideally, TFP should be conceived as that part of output that is not explained by the amount of labor and capital used, i.e. as the residual from (1):

$$A_{it} = f^{-1}(Y_{it}, L_{it}, K_{it}) \tag{2}$$

Therefore, even if not directly observed, it can be estimated according to (2). TFP can be thought of as a black box containing several aspects of the firm, such as its organizational, logistic and productive efficiency. It is arguably influenced by many factors, ranging from the labor policies carried out by the firm (e.g. the use of part-time work, PT_{it}), to firm strategies such as R&D investments, exports and FDIs:

$$A_{it} = h(PT_{it}, ...) \tag{3}$$

It should be noticed that, according to our framework, part-time labor enters the production function through the TFP. This implicitly amounts to assume that the *labor* productivity does not differ between between part-timers and full-timers, while part-time work only affects the organizational efficiency of the firm (captured by TFP). As discussed in Section 2, the potential channels through which part-time work impacts on TFP are essentially two: decreased productivity due to communication and transaction costs and increased productivity due to allocation efficiencies in the staffing of the workforce.

Although it would be possible to examine the effect of part-time on TFP by directly estimating (1), due to data-related motivations which will be illustrated later, we prefer to proceed in two steps. From the first step we recover TFP estimates according to (2). In the second step we analyze the impact of part-time work on TFP estimating (3).

In the first step, we assume that the production function in (1) is a log-transformed Cobb-Douglas. In order to allow for structural differences in the production process among industries, we estimate a separate production function for each industry, as defined by the 2-digit Ateco 2002 classification. In total, we estimate 40 different production functions. A relevant issue in the estimation of production functions is the (positive) correlation between inputs and the unobserved TFP. The more a firm is productive, the more it uses labor and capital inputs. This issue, commonly known as the 'simultaneity problem', makes OLS estimates inconsistent. In order to solve it, several solutions have been proposed. If one is willing to assume that firm productivity is constant over time, fixed-effects (FE) estimation solves the problem. However, this assumption seems unrealistic. Therefore, several control function methods have been developed that allow firm productivity to follow a more flexible (i.e. time-varying) process. Olley and Pakes [1996] (OP) are the first to propose to proxy unobserved productivity through firm's investment demand. Levinsohn and Petrin [2003] (LP) propose instead to use the firm's demand for intermediate goods as a proxy for productivity. They argue that it is more suitable than the demand for investments, essentially because it is more reactive to productivity shocks, hence abler to capture them. In order to solve a major drawback of the LP method, related to collinearity issues, Ackerberg et al. [2006] (ACF) propose a modified version of it, in which all the estimates of the production function parameters are recovered in the second step of the estimation procedure. Starting from the ACF method, we go further developing a version of it that explicitly accounts for firm-specific fixed effects (ACF-FE). We argue that this procedure is abler than ACF in delivering consistent estimates basically because, removing unobserved heterogeneity, allows the productivity proxy to work better. In the empirical analysis we perform OLS, FE, LP, ACF and ACF-FE estimation.[6] All the estimations include year, region, industry and year interacted by industry dummies (industry is defined according to the 3-digit Ateco 2002 classification). We then compute the corresponding TFP estimates according to (2). In view of the considerations previously made, TFP estimates obtained from the the ACF-FE estimation are elected as our reference measure of firm productivity. Appendix A provides a detailed discussion of the estimations performed in the first step.

In the second step we explore the impact of part-time on TFP. The regression model that

[6]OP is unfeasible for us, since we do not have (reliable) data on investments.

we are going to estimate, which was in its general form in (3), is now rewritten as:

$$\widehat{TFP_{it}} = a + \theta PT_{it} + \gamma V_{it} + \delta D_{it} + u_{it} \tag{4}$$

where: PT_{it} is the amount of part-time used by the firm[7] and is our regressor of interest; V_{it} is a vector collecting some variables included as controls (e.g. female share, migrant share and temporary share); D_{it} is a set of dummy variables aimed at controlling for productivity differentials over time, industry (at the 3-digit level), time *and* industry (i.e. interaction dummies), region and firm size; while u_{it} is simply the error term of the regression, possibly correlated with part-time. In particular, one may argue that some unobservable time-invariant and firm-specific characteristics, such as the managerial ability, besides contributing to determine firm productivity, also influence the share of part-time actually used. One may think that more skilled managers, while allowing firms to reach a higher level of productivity, are also more prone to accommodate for worker's request for shorter working time. Similarly, one may argue that the use of part-time work is influenced by productivity shocks. It may be the case, for instance, that in bad times firms 'convert' some of their full-time employees into part-timers, in order not to fire them. Fixed-effects and instrumental variable (IV) estimations, compared to simple OLS one, allow to assess if it is indeed the case.

4 The Italian Case

In all the industrialized countries, including Italy, part-time work started to be increasingly used since the middle of the 1970s. As Kalleberg [2000] points out, the main determinants for its constant growth have to be found in the increased uncertainty of the general economic conditions and in the (consequent) sharpened competition among firms, which eventually leaded them to prefer flexible working arrangements such as part-time and temporary work. At the same time, national labor laws, often designed to protect standard workers (i.e. full-time and not temporary), have contributed to the growth of part-time work, intended as a way for firms to escape costs and legal duties associated with these laws. Demographic changes in the composition of the labor force played a fundamental role, too: the rise in married women workers and older workers, attracted by the flexibility characterizing part-time work, are the two most straightforward examples.

According to Eurostat, 19.2% of the European employees worked part-time in 2010. In Italy, the part-time share was around 15%, a percentage similar to Spain and France.

[7]In the empirical analysis, it is defined as the share of part-timers over the total number of employees.

Many studies stressed how part-time acts as an instrument of work-life balance, allowing people to better conciliate work with private life needs. Since women are usually the ones involved in family care and household activities, it is not surprising that part-time jobs are covered for the great majority by women. Similarly to the rest of Europe, in Italy, the incidence of part-time among employed women was 29% in 2010, while only 5.5% for men.

Data provided by ISFOL[8], suggest that part-timers are overrepresented into young age groups and that female part-timers are overrepresented into the central age category, presumably because this is the age in which women have children. If for women the incidence of part-time is biggest among the low-educated category, the contrary happens for males. While part-timers are generally segregated into low-skilled jobs, in the trade and services sectors they are overrepresented into high-skilled occupations. Finally, part-timers are segregated into temporary contracts and into trade and household services sectors.

According to OCSE, Italy is in the first positions, together with Spain and Portugal, in the incidence of the so called 'involuntary part-time': if the EU-15 percentage of part-timers declaring to be employed on a part-time basis against their will was 20.6% in 2010, it raised up to 39.3% in Italy. Together with involuntary part-time employment, there coexists a phenomenon which can also be referred to as 'involuntary part-time' to all intents and purposes. Many firms[9] use part-time work in order to accommodate for the workers' requests for shorter working hours and would rather prefer to employ their part-time workers on a full-time basis. The fact that many part-timers would prefer to work full-time while, at the same time, many firms employing part-timers would prefer to employ them on a full-time basis, casts light on a substantial misalignment between the demand and supply of part-time labor, which eventually leads many workers and firms to be unsatisfied.

In Italy, part-time received a first and bare regulation only in 1984. Subsequently, thanks to the implementation of the European Directives concerning part-time work, it has been regulated more systematically on several occasions: in 2000, in 2003, with the so called 'Biagi's law', and in 2007.

The regulation of part-time work is based on the principle of an equal treatment between part-time and full-time workers, both in relation to the hourly pay and to annual leaves as well as other kind of non monetary benefits. According to the Italian legislation, the reduction of working hours can occur in three ways: the horizontal model, where the employee works all the working days with a reduction in the daily working time; the vertical model, where the employee works full-time, but only on some days of the week, month or year; and the

[8]In particular, we are referring to the ISFOL PLUS 2008, a large survey conducted on about 40,000 Italian men and women.

[9]According to the RIL survey conducted by ISFOL in 2010, collecting a representative sample of all the Italian firms, they are about 60%.

mixed model, which is a combination between the horizontal and the vertical part-time model. Part-time work contract should contain a clear and precise determination of the working time, with respect to the day, week, month and year. Working time can be made flexible through the use of the so called 'flexible' and 'elastic clauses'. Flexible clauses give the possibility to modify the *collocation* of the daily working hours in the case of horizontal part-time contracts, whereas elastic clauses can be used for extending (and not curtail) the number of working hours in the vertical part-time. The procedures for the use of such clauses are provided by the law and by the sectoral labor collective agreements.

The general trend in the regulation of part-time work has been, on the one hand, in the direction of a systematic and structured discipline and, on the other hand, toward the attainment of a greater flexibility and discretion in the signing of part-time work contracts. Compared to the early regulations (in 1984 and 2000), the Biagi's Law and, less extensively, the legislative decree in 2007 have moved towards a greater flexibility in the working time arrangements and less restrictions to carry out additional and overtime work as well as to stipulate flexible or elastic clauses. Moreover, they have left room for collective bargaining, which, integrating the legal regulation, concretely rules part-time work. However, as we shall see later in the discussion, the legislative decree in 2007, though in general oriented to increasing part-time work flexibility, strongly reduced the power of firms with respect to the signing of the elastic and flexible clauses introduced by Biagi's Law.

5 Data

In order to assess the impact of part-time work on TFP, we use three waves (2005, 2007 and 2010) of the RIL survey, a uniquely rich data source provided by ISFOL. Each wave of the RIL survey interviews about 23,500 private sector Italian firms, including both partnerships and corporations. Since some firms are followed over time, the (complete) RIL dataset is partially panel. The main variables surveyed refer to the structure of the workforce, the reasons for which the firm uses certain work contracts (e.g. part-time and temporary work), the employment of non-EU workers, the recruitment methods, the industrial relations and the innovations and investments undertaken.

However, since the RIL dataset does not provide balance sheet information, we resort to another dataset in order to get TFP estimates for the RIL's firms.[10] For this purpose, we use the AIDA dataset for the period 2000-2010. It is provided yearly by the Bureau Van Dijk and contains comprehensive balance sheet information on all the Italian corporations operating

[10]The RIL dataset only provides information on employees and revenues, whereas information on physical capital and intermediate inputs, necessary to estimate production functions, is not available.

in the private sector, except for the agricultural and financial industries. Using the AIDA dataset to get the TFP estimates produces some positive side effects. Thanks to its width (about 2,5 million observations) it is possible to still get precise estimates, while estimating 40 different production functions. Moreover, the relatively long panel allows the methods exploiting the time dimension (i.e. all but OLS) to perform better. Appendix B, besides showing some summary statistics of the AIDA dataset, provides a detailed description of the variables used in the estimation of the production functions.

Through the national tax number (*codice fiscale*), that uniquely identifies each firm in both datasets, it is possible to match the TFP estimates recovered from AIDA with the RIL's firms. Out of 37,302 potential matches (this is the number of corporations in the original version of the RIL dataset), 22,005 are actually matched with the TFP estimate from the AIDA dataset. We will refer to the resulting dataset as of the 'RIL-AIDA' dataset. The merge rate is about 60%. An 'acceptable' rate, if we consider that AIDA does not contain data for the agricultural and financial sectors firms, while RIL does, and that, beside a very basic cleaning procedure (described in Appendix B), we are forced to remove the AIDA observations with missing, negative or zero values of the variables used in the production function, which are unfortunately many.

In addition to an essential cleaning of the RIL-AIDA dataset aimed at removing observations with missing values in the variables used in the estimations[11], we decide to restrict the attention to firms with at least 10 employees. The rationale behind this decision is twofold. In the first place, it is in order for the part-time share to make sense. In the second place, since we are interested in the effect of part-time on the organizational efficiency of the firm, it is reasonable to consider firms with a sizeable organizational structure.

The final version of the RIL-AIDA dataset used in the second step is made of 13,860 firm-year observations for 9,405 firms.

The top panel of Table 1 shows that the manufacturing sector is by far the most numerous, covering almost 50% of observations. Services and trade sector represent about 18% of observations. While the rest is split between the construction sector (14.4%) and the transportation and telecommunication industry (8%). The lowest panel of Table 1 shows that for about 63% of the firms we have only one observation, while about 11% of them are observed over the the full observation window.

Table 2 presents some summary statistics of the RIL-AIDA dataset. On average, firms' revenues are 33 million Euros per year, but for 50% of observations they are lower that 5 million Euros. The average number of employees in the firms is 104, but for half of them (75%) this figure is less than 29 (69). The significant difference between average

[11]This data trimming causes 1,886 observations to be removed from the sample.

and median values, suggests that, besides some big firms, small- and medium-sized firms represent the great majority. On average, 31% of employees are female, 6% originate from non-EU countries, while 10.5% are employed on a temporary basis. About 59% of them are blue-collars, 36% are white-collars and about 5% fill a managerial position. The great majority of workers in the average firm are low- or medium-educated, while only 8.8% of them has a college degree; on average, half of the workforce is in the age comprised between 35 and 49 years.[12]

On average, firms employ 8,4% of their workforce on a part-time basis. Among part-timers, in the average firm, 79% are women, while only 21% are men. Hence, our dataset is in line with the fact that part-time jobs are mainly covered by women. Horizontal part-time is by far the most widespread type of part-time used by firms: on average, 87% of part-times are have an horizontal part-time contract, while the corresponding figures for vertical and mixed part-time are 7% and 6% respectively. In particular, horizontal female part-time employees represent the most common type of part-timers, accounting for about 70% of the total part-timers in the average firm. Table 3 shows that part-time is used by the great majority of firms: about 68% of them employs at least one worker on a part-time basis. On the contrary, the use of (elastic and/or flexible) clauses is not so pervasive: only 37% of firms using part-time work do adopt clauses. Excluding firms using mixed part-time work, it is possible to notice how the incidence of clauses vary according to the type of part-time: 34% of firms using horizontal part-time applies flexible clauses, while 39% of firms using vertical part-time applies elastic clauses.[13] The bottom panel of Table 3 summarizes the answers given by firms employing some part-timers about the main reason why they indeed use part-time work. The vast majority of them (68%) declares to use part-time for accommodating for workers' requests for shorter working time.[14] The remaining 32% is split between those who willingly use it (30%) and those who give answers different from the proposed alternatives (2%). Among the firms that declare to use it willingly, the main reasons have to do with the suitability of part-time work with the production process (20.7%) and with the the impossibility to employ workers full-time because of budget constraints (4.8%). Some firms choose part-time work because they believe that part-timers are more productive than full-timers (2.46%) and in order to face programmed seasonality (2.05%).

[12] Data on the education and age distribution of the employees in the firm are available only for 2010.

[13] Since mixed part-time is a combination of horizontal and vertical part-time, both flexible *and* elastic clauses can be applied in this type of contract. Whereas, flexible clauses *only* applies to horizontal part-time while elastic clauses *only* applies to vertical part-time.

[14] This happens in all the the macro-industries, i.e. manufacturing, construction, trade, transportation and communication and services.

6 Results

6.1 Main Finding

In this Section, we will explore the impact of part-time work on TFP.

Recall that we first recover the TFP estimates from the AIDA dataset and then we match them with the RIL's firms. As we mentioned before, in order to allow for structural differences in the production process, we estimate 40 different production functions (one for each 2-digit Ateco 2002 sector). Moreover, note that, since we perform OLS, FE, LP, ACF and ACF-FE estimations of the production functions, we get the corresponding 5 measures of TFP. Since our preferred estimation method for the first step is ACF-FE, we will use the ACF-FE estimates of the TFP as the dependent variable in all the following second-step estimations (i.e those analyzing the impact of part-time work on TFP). Appendix C discusses TFP estimates in more detail.

Table 4 presents results for the impact of part-time on TFP. The full set of results includes 11 different specifications and/or methods to estimates Equation (4).

The first column shows OLS estimates of (4) with only a basic set of controls: size, year, industry, year and industry interaction and region dummies. According to this basic regression, part-time work has a strongly significant negative impact on firm productivity: one standard deviation increase (0.141) in the part-time share causes the firm productivity to decrease by 3.04%.[15]

However, as we have pointed out in Section 4, since part-time workers are segregated with respect to gender, jobs and type of contract (i.e. temporary *versus* not temporary), it is safe to also control for these workforce characteristics. This is done in Specification (2), that, besides the controls of (1), adds the female-share, the migrant-share, the share of temporary workers and of blue- and white-collar workers. According to this model, part-time still has a negative and significant impact on TFP, though smaller: one standard deviation increase in part-time share brings about a reduction in the firm productivity of about 2.03%. Results suggests that, besides being (in general) positively correlated with part-time share, these workforce characteristics are negatively related with the TFP.[16] Thus, if we fail to control for them, we tend to overestimate the negative impact of part-time on TFP.

Moreover, we also know that part-timers are segregated by age and by education. Even though we are not able to account for the age and education distribution of the workforce

[15] Recall that par-time share is measured as the number of part-time employees over the total number of employees. For an average firm that employs 100 workers, one standard deviation increase in the part-time share corresponds to an increase in the number of part-timers from 8 to 22.

[16] In the sample, female, white-collar, migrant and temporary shares are positively correlated with part-time share, while the correlation with blue-collar share is negative but very small (-0.006).

in the whole sample, we can still do it for year 2010 (Specification (3)). As discussed in Section 3, the management ability and characteristics may as well influence both the level of part-time and the TFP. Even though only for the year 2010, we are able to account for several managerial characteristics: the type of the manager (i.e. whether he is the owner of the firm or an internal/external manager), his gender, education and age (Specification (4)). Comparing Specification (5), which reproduces Specification (2) but only for year 2010, to Specification (3) and (4), we can see how these sets of controls do not substantially change the estimate: -0.182 in both (3) and (4) *versus* -0.192 in (5). This casts light on the minor issue of age and education, and, most importantly, of management characteristics. Still, one can argue that it is indeed the unobservable part of them which precludes from the identification of the causal effect of interest. We can investigate whether it is the case by performing FE estimation on Equation (4). According to Specification (6), only including year and year/industry interaction dummies, the effect of part-time work on TFP is still negative and significant at 10% level. Specification (7) adds the usual workforce controls, i.e. female, migrant, temporary, blue- and white-collars shares. The estimated coefficient is very similar with respect to the first FE specification (-0.115 *versus* -0.117) and still significant at 10% level. For comparative purposes, Specification (8) performs an OLS regression as in (2), but on the sample used in the FE estimation. Though the estimated coefficient associated with part-time is a bit higher in absolute terms with respect to the FE one (-0.169 *versus* -0.117), we argue that the unobservable managerial ability (as well as all the other unobservable time-invariant firm-specific characteristics) does not represent a real threat in the identification of the object of interest.[17] For what concerns the fact that the FE estimates of part-time coefficient have generally higher p-values with respect to their OLS counterparts, we argue that the cause is twofold. On the one hand, since for FE to be performed are needed at least 2 years of observations for a single firm, about half of the sample is removed, thus dramatically reducing the sample size. On the other hand, for firms having a panel dimension, the number of observations is most of the time 2 and, at best, 3, a small number for efficiently estimating the coefficient of interest only exploiting the within-firm variation.

As discussed in Section 3, it may also be that part-time work is correlated with the idiosyncratic productivity shock, causing it to be endogenous and hence hindering the identification of the causal effect. In order to explore this possibility, we perform a simple IV estimation on Equation (4), where we instrument part-time with its lag. In practice, in the equation for year 2010, we instrument part-time share with the its level in 2007 and, in the equation for year 2007, with its level in 2005. Notice that in order to perform this

[17] Moreover, FE estimates are known for delivering coefficients biased toward 0, because of the exacerbation of the measurement error induced by the within-firm transformation.

kind of IV estimation, we loose one year of observations, i.e. 2005, and that we are forced to consider firms with at least 2 years of consecutive observations. This sharply cuts our sample: about 75% of observations cannot be used in the IV estimation. The results for this IV estimation are presented in column (9) of Table 4. The predicted impact of part-time work on TFP is still negative, significant at 1% level and equal to -0.273. Since this model is exactly identified, we cannot assess the validity (i.e. the exogeneity) of the instrument used. In order to gain insights on this issue, we perform another IV estimation which, besides instrumenting part-time with its own lag, adds other instruments constructed on the basis of the method proposed by Lewbel [2012]. This approach serves to identify parameters in models with endogenous regressors, when external or internal instruments are lacking; or, alternatively, in order to gain overidentification for testing the validity of the orthogonality conditions, i.e. in our case. Identification is achieved by having instruments that are uncorrelated with the product of heteroskedastic errors. In practice, the first step is to run an OLS regression on the endogenous regressor (in our case part-time share) against all the exogenous regressors in the model. Then residuals obtained from this regression are used to construct the instruments from:

$$Z_j = (X_j - \bar{X}) \cdot \epsilon \tag{5}$$

where ϵ is the vector of the first-stage residuals, X_j is the vector of observations for the exogenous regressor j, $\bar{X}$ is its mean, and Z_j is the instrument generated from regressor X_j. Besides the lag of part-time, we decide to use 5 additional instruments constructed on the basis of Equation (5) from female, migrant, temporary, blue- and white-collar share. With these 6 instruments for part-time share, we can then perform the standard IV estimation (Specification (10)). The estimated coefficient is again negative, significant at 1% and equal to -0.252. The Hansen-J test for the validity of the overidentifying restrictions indicates that they are overall valid (p-value 0.806). As before, for comparative purposes, we run the usual OLS regression on the sample used in the IV estimation (Specification (11)). Comparing IV estimations with the appropriate OLS estimation, we can see how also correlation of part-time with the time-varying productivity shock does not represent a big issue in practice. Estimates of the impact of part-time on TFP are always negative and quite similar: -0.273 and -0.252, for IV estimations *versus* -0.195, for the OLS one.

On the one hand, our main result is line with Specchia and Vandenberghe [2013] who focus on the private sector Belgian firms in the period 2002-2009. In particular, while they find that a ten percentage point increase in the part-time share causes firm productivity to decrease by 1.3% (0.7%) for long (short) part-timers, we find that the same same figure to be slightly higher: 1.45%.[18] On the other hand, Garnero et al. [2014], again for private sector Belgian firms for the period 1999-2010, draw an opposite conclusion: they find that part-time is beneficial for firm productivity.

As an aside, notice that increases in the shares of females, migrants, blue- and white-collars (with respect to managers) are generally associated with a decrease in the TFP. On the contrary, the share of temporary, young (under-35) and highly educated workers is positively correlated with TFP. Our results also suggest that having an internal/external manager is better than when the owner of the firm also manages it. Female managers seem to do less than their male counterparts, and the same is for young managers (under-40). Results also show that TFP increases with the firm size. Small firms (between 10 and 19 employees) are estimated to be less productive by as much as 59.1% with respect to large firms (more than 250 employees). The same figure is 50.3% for medium-sized firms (between 20 and 49 employees) and 33.4% for medium-large firms (between 50 and 249 employees).

Summarizing, we find that part-time work has a negative impact on firm productivity. Moreover, not accounting for the age and education distribution of the workforce and management characteristics, on the one hand, as well as unobserved firm-specific fixed-effects and correlation of part-time with productivity shock, on the other hand, is unlikely to represent a real threat in the identification of the effect of interest. In view of this consideration and given that OLS estimation allows to exploit the full sample, we take Specification (2) as our reference, for both assessing the effect of part-time work on productivity, as just discussed, and for our extensions, which are discussed below.

6.2 Extensions

Up to here, we have found that part-time work is generally detrimental to firm productivity. This finding is coherent with the idea that part-time work causes information, communication and organizational inefficiencies which eventually translate into productivity losses.

We now concentrate on some extensions, which, at least to our knowledge, have never been explored so far.

Table 5 shows the OLS estimates of the separate impact of horizontal, vertical and mixed part-time work. Not surprisingly, since it represents most of the part-time work, horizontal part-time is estimated to have a negative and virtually the same with respect to the general case (-0.148 *versus* -0.146) impact on the TFP. This result is strongly significant (at 1% level). Vertical part-time is also estimated to have a negative impact, though very small in magnitude (-0.013) and not significantly different from zero at any conventional level. This

[18] We cannot distinguish between long and short part-timers.

result casts light on the fact that what really threatens organizational efficiency of the firm is working shorter hours each day, while working full-time on only some days of the week does not seem to do so. Mixed part-time is predicted to have a negative and significant impact on TFP (-0.197): being it a mixture of the horizontal and vertical model, it is presumable that its effect is carried out by the horizontal component.

In Table 6, we analyze whether the impact of part-time on TFP is different if the firm passively accepts it as a consequence of the workers' requests for shorter hours with respect to the case in which it willingly chooses to use it. In order to answer this question, we divide the sample of firm-year observations using part-time work into two sub-samples: those using part-time as the result of the workers' willing and those which choose to adopt it.[19] Results are consistent with our conjecture: firms 'forced' to use part-time are the ones suffering the most from it. Indeed, a 10 percentage point increase in the part-time share is estimated to reduce TFP by about 2.5% in this case. On the other hand, the same increase for the case in which firms willingly choose to use part-time would decrease TFP by only 1.3%. What is surprising, is that part-time is also harmful for those firms that willingly choose it.[20] We argue that this may be due to the fact that, in general, managers fail to realize that part-time is indeed hurting their productivity. However, it may as well be the result of a consciously weighed trade-off between productivity losses and costs savings, to the extent to which part-timers are discriminated against in terms of hourly pay.

Table 7 investigates whether the impact of part-time on productivity is different if the firm utilizes elastic and/or flexible clauses or not. As before, we split the sample of firm-year observations using part-time into two groups: those using part-time with clauses and those which do not. We find evidence that using clauses helps in cushioning the negative effect of part-time. They contribute to reduce its negative impact by about 43%. In particular, a 10 percentage point increase in the part-time share is estimated to bring about a decrease in TFP by 1.07% in the case in which clauses are used, whereas the same increase causes TFP to decrease by about 1.89% in the case where clauses are not used. This result casts light on the effectiveness of clauses: instruments intended at increasing the flexibility for the firms in the use of part-time and, hence, at making them more willing to use it, in the perspective of allowing people to better conciliate work and private life. However, if the Biagi's Law was in the direction of a great freedom in the use of clauses by firms, thus favoring them at the expenses of employees, with the subsequent law in 2007, the situation has shifted in favor of employees. Indeed, since then, the *precise* procedure for using elastic and flexible

[19]Notice that we have to remove observations that use part-time but choose the 'other reason' item, since we do not know whether they belong to the first or to the second group.

[20]Even removing from the sample firms declaring to use part-time because they cannot afford to keep the workers on a full-time basis, which in a sense makes them forced to use it, does not change the result.

clauses have to be agreed on the basis of sectoral collective agreements, in which the needs of individual firms cannot be directly incorporated.[21] This eventually contributes to make firms less willing to accord part-time work to workers who ask for it. Our finding suggests that, introducing more flexibility in the use of part-time could be a win-win strategy: for firms, which would experiment a lower loss in productivity associated with part-time, and for workers, since firms would be more willing to employ on a part-time basis those who would like to and that by now are not able to do so. In order to gain further insights on the potential for clauses to reduce productivity losses associated with part-time, the lowest part of Table 7 presents results of the separate estimation on waves 2005 and 2007 (i.e. before the part-time reform of 2007[22]) and on wave 2010 (i.e. after the reform). Results suggest that when the Biagi's Law was in force (2005 and 2007), using part-time with clauses decreases TFP by about 47% less than using it without clauses; whereas using part-time with clauses in 2010, when the power of firms in relation to the use of clauses has been strongly reduced as a result of the 2007's Law, is estimated to decrease TFP by about 37% less with respect to the case in which clauses are not used. Hence, the capability of clauses to curtail productivity inefficiencies caused by part-time has been substantially reduced as the result of the 2007's Law, by as much as 10 percentage points.

Table 8 summarizes results for the separate impact of part-time on TFP by sector of economic activity. We find that part-time work damages firm productivity in all the macro-categories of industries: manufacturing, construction, trade, transportation and communication and services. The impact of interest is always statistically significant (at least at 10% level), and ranges between -0.122 (for manufacturing) and -0.467 (for transportation and communication). When we drill down and consider several sub-industries, we find that only for the retail sector the impact of part-time on TFP changes its sign, becoming positive, though very small in magnitude (0.006). This result is to be expected if we consider that often retail shops have opening hours longer than the typical full-time working time and that they may as well experiment workload peaks during the day, so that part-time work may represent a potential for allocation efficiency gains. This result is in line with [Künn-Nelen et al., 2013], who, focusing on the Dutch pharmacy sector (which belongs to the retail sector), find that part-time is beneficial to firm productivity. However, the effect found here is not statistically significant at any conventional level, thus not allowing to conclude with certainty this result.[23]

Appendix D provides some robustness checks. We consider the impact of interest only for

[21] The Biagi's Law allowed the employers and the employees to directly stipulate flexible and elastic clauses, even in the absence of collective agreements. Since 2007, this is no more permitted.

[22] Since this reform has been enacted on December 24th, it has virtually started to be applied since 2008.

[23] We only have 346 observations for the retail sector.

the period before the crisis (i.e. years 2005 and 2007). Moreover, we compare the estimated impact of part-time on TFP when different TFP estimates are used.

7 Conclusions

In this paper we investigate the impact of part-time work on firm TFP through a two-step procedure. In the the first step, we use a large panel dataset on (almost) all the Italian corporations for the period 2000-2010 to recover a TFP estimate for each firm-year observation. We deal with the simultaneity issue concerning the estimation of production functions through the ACF-FE method, which explicitly takes into account unobserved firm heterogeneity. We then match the TFP estimates with a uniquely rich survey on Italian firms for the years 2005, 2007 and 2010. In the second step of the procedure, we explore the impact of part-time work on TFP.

Our main finding is that part-time work is detrimental to firm productivity: one standard deviation increase in the part-time share is estimated to decrease TFP by about 2%. Our emphasis for this result is on the information inefficiencies created by part-time, which bring about increases in communication and transaction costs, eventually leading to a decrease in productivity.

We also explore the separate impact of horizontal, vertical and mixed part-time, finding that the negative impact of part-time is mostly carried out by the horizontal component, while for the vertical model we find no significant impact. This leads us to conclude that what really hurts the firm is the *daily* reduction in the working time.

Moreover, we find that firms forced to use part-time are the ones suffering the most from it: the negative impact of part-time on those firms is almost double with respect to that on firms willingly adopting it. While this difference is consistent with expectations, we think that the fact that part-time is harmful also for firms that choose it on purpose is somewhat surprising. We argue that this may be due to the inability of managers to recognize it. However, it may as well be the result of a consciously weighed trade-off between productivity losses and costs savings, to the extent to which part-timers are discriminated against. Even if there is some evidence for employers' rents associated with part-time in Belgium, as found by Garnero et al. [2014], at least to our knowledge, there are no studies focusing on part-time discrimination for the Italian case, thus leaving the above discussion open as well as an open door on future research on this topic.

We then concentrate on the role of flexible and elastic clauses. In general, we find that clauses are effective in reducing productivity losses associated with part-time: using clauses is estimated to reduce its negative impact by about 43%. Considering that most of the firms declare to be forced to use part-time work in order to meet employees' requests for shorter hours, clauses represent an important way in which firms can increase flexibility in the stodgy usage of part-time. This eventually translates into a productivity gain associated to clauses. It should be noticed, however, that, though beneficial clauses might be, still using part-time work is harmful for firm productivity, although to a lesser extent with respect to the case in which they are not used. Since in December 2007 a Law restricting the power attributed to firm in the use of clauses has entered into force, we can investigate to what extent this has influenced the role of clauses. We find evidence that the Law has contributed to decrease the potential for clauses to alleviate the negative impact of part-time: if the differential in the impact between firms using clauses and firms not using them was in the range of 47% before the reform, it has been reduced to about 37% after. If this certainly represents a 'bad news' for firms, the impact on the workers' welfare is less clear. On the one hand, the decrease in the power for firms to stipulate clauses may have led some of them to reduce the use of part-time, hence not according part-time to employees asking for it. On the other hand, it may as well have provided more constraints in order not to make part-time work a full-time one in disguise. Since our paper focuses on firms, we do not explore the supply side, which could be an interesting issue for future research.

Table 1: **RIL-AIDA dataset: Distribution of observations by sector of economic activity and number of observations**

Sector of economic activity	**Frequence**	**Percentage**
Manufacturing	6,897	49.76
Construction	2,002	14.44
Trade	1,46	10.58
Transportation and Communications	1,111	8.02
Services	2,383	17.19
Total	13,860	100
Number of observations	**Firms**	**Observations**
1	5,967	5,967
2	2,421	4,842
3	1,017	3,051
Total	9,405	13,860

Source: RIL-AIDA dataset (years: 2005, 2007 and 2010)

Table 2: **RIL-AIDA dataset: Sample summary statistics**

Variable	**Mean**	**Std. Dev.**	**1st Q.**	**Median**	**3rd Q.**
Information from AIDA dataset					
Revenues	33,123,111	207,185,847	2,072,153	4,984,099	15,364,193
Value Added	7,611,426	33,644,799	680,148	1,445,422	4,015,138
Personnel costs	4,596,118	18,639,319	483,370	1,001,541	2,604,675
Wages	3,179,241	12,991,786	340,868	700,014	1,823,686
Capital*	6,067,997	41,796,696	163,482	663,540	2,615,590
Raw materials	17,784,712	146,538,303	444,044	1,539,676	6,046,541
Profit	795,510	16,413,536	152	32,194	214,378
Information from RIL dataset					
Employees	103.709	396.895	15	29	69
Female share	0.306	0.245	0.105	0.233	0.462
Migrant share	0.058	0.110	0	0	0.068
Temporary share	0.105	0.153	0	0.055	0.140
Blue-collar share	0.593	0.299	0.400	0.692	0.822
White-collar share	0.361	0.279	0.152	0.268	0.533
Managers share	0.046	0.078	0	0.009	0.066
College share**	0.088	0.139	0	0.042	0.101
High-school share**	0.418	0.253	0.214	0.370	0.600
Middle-school share**	0.495	0.297	0.24	0.545	0.750
Under 25 share**	0.056	0.087	0	0.020	0.083
25-34 share**	0.244	0.179	0.118	0.208	0.333
35-49 share**	0.510	0.192	0.400	0.514	0.629
Over 50 share**	0.189	0.148	0.081	0.167	0.273
Information from RIL dataset: part-time work					
Part-time share	0.084	0.141	0	0.040	0.098
Female part-time share	0.065	0.115	0	0.026	0.081
Male part-time share	0.019	0.058	0	0	0.009
Horizontal part-time share	0.070	0.126	0	0.029	0.083
Vertical part-time share	0.006	0.035	0	0	0
Mixed part-time share	0.008	0.051	0	0	0

Table 2: **RIL-AIDA dataset: Sample summary statistics - continued**

Variable	**Mean**	**Std. Dev.**	**1st Q.**	**Median**	**3rd Q.**
Horizontal female part-time share	0.056	0.104	0	0.018	0.071
Vertical female part-time share	0.004	0.026	0	0	0
Mixed female part-time share	0.005	0.039	0	0	0
Horizontal male part-time share	0.015	0.051	0	0	0.002
Vertical male part-time share	0.002	0.016	0	0	0
Mixed male part-time share	0.002	0.022	0	0	0
Female share inside part-time	0.791	0.321	0.667	1	1
Male share inside part-time	0.209	0.321	0	0	0.333
Horizontal part-time share inside part-time	0.868	0.294	1	1	1
Vertical part-time share inside part-time	0.070	0.215	0	0	0
Mixed part-time share inside part-time	0.062	0.214	0	0	0
Horizontal female share inside part-time	0.699	0.375	0.500	0.909	1
Vertical female share inside part-time	0.046	0.172	0	0	0
Mixed female share inside part-time	0.046	0.180	0	0	0
Horizontal male share inside part-time	0.170	0.297	0	0	0
Vertical male share inside part-time	0.024	0.118	0	0	0
Mixed male share inside part-time	0.016	0.100	0	0	0

Number of firm-year observations: 13,860

Number of firms: 9,405

Source: RIL-AIDA dataset (years: 2005, 2007 and 2010)

* Computed according to the Permanent Inventory Method. See Appendix B for details.

** Only for year 2010 (5,912 observations).

Table 3: **RIL-AIDA dataset: Part-time work. Use, types, clauses and reasons**

	Frequence	**Percentage**
Use of part-time and clauses		
Yes	9,434	68.07
of which:		
with clauses (elastic and/or flexible)	3,467	36.75
without clauses (elastic and/or flexible)	5,967	63.25
Types of part-time		
Horizontal part-time use	8,710	62.84
Vertical part-time use	1,407	10.15
Mixed part-time use	1,061	7.66
Flexible and Elastic Clauses - excluding firms using mixed part-time		
Horizontal part-time use	8,041	62.83
of which:		
with Flexible clauses	2,721	33.84
without Flexible clauses	5,320	66.16
Vertical part-time use	1,169	9.13
of which:		
with Elastic clauses	459	39.26
without Elastic clauses	710	60.74
Reasons for the use of part-time		
Workers' willing	*6,411*	*67.96*
for accommodating workers' requests for shorter working time	6,411	67.96
Firms' willing	*2,828*	*29.98*
it's suitable for the production process	1,954	20.71
it's not affordable to employ workers full-time	449	4.76
it increases labor productivity	232	2.46
for facing programmed seasonality	193	2.05
Other reason	*195*	*2.07*
Other reason	195	2.07

Source: RIL-AIDA dataset (years: 2005, 2007 and 2010)

Table 4: **Results; basic model (part-time work); estimation methods: OLS, FE, IV**

	Dependent variable: $\widehat{TFP}_{it}$ - ACF-FE estimates										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Variable	**OLS1**	**OLS2**	**OLS2010a**	**OLS2010b**	**OLS2010c**	**FE1**	**FE2**	**OLS-comp1**	**IV1**	**IV2**	**OLS-comp2**
Part-time share	-0.219***	-0.146***	-0.182***	-0.182***	-0.192***	-0.115*	-0.117*	-0.169***	-0.273***	-0.252***	-0.195**
	(0.030)	(0.031)	(0.049)	(0.049)	(0.049)	(0.063)	(0.066)	(0.055)	(0.104)	(0.095)	(0.078)
Female share		-0.089***	-0.137***	-0.128***	-0.115***		0.017	-0.126***	-0.144***	-0.148***	-0.158***
		(0.022)	(0.037)	(0.037)	(0.037)		(0.039)	(0.028)	(0.041)	(0.040)	(0.040)
Migrant share		-0.123***	-0.102*	-0.080	-0.094		0.008	-0.117***	-0.099	-0.099	-0.100
		(0.033)	(0.059)	(0.059)	(0.059)		(0.046)	(0.044)	(0.064)	(0.064)	(0.067)
Temporary share		-0.049*	-0.027	-0.018	0.026		0.161***	0.068	0.140**	0.140***	0.141**
		(0.025)	(0.039)	(0.039)	(0.039)		(0.042)	(0.042)	(0.057)	(0.057)	(0.059)
Blue-collars share		-0.682***	-0.600***	-0.550***	-0.781***		-0.072	-0.931***	-0.854***	-0.856***	-0.861***
		(0.063)	(0.106)	(0.105)	(0.106)		(0.068)	(0.103)	(0.140)	(0.140)	(0.146)
White-collars share		-0.526***	-0.433***	-0.392***	-0.542***		-0.074	-0.772***	-0.554***	-0.556***	-0.563***
		(0.065)	(0.111)	(0.111)	(0.114)		(0.069)	(0.107)	(0.149)	(0.150)	(0.156)
Under-25 share			0.166**	0.184**							
			(0.0787)	(0.079)							
25-34 share			0.094**	0.107**							
			(0.044)	(0.044)							
35-49 share			0.062	0.073*							
			(0.044)	(0.044)							
High-school share			0.011	0.005							
			(0.026)	(0.026)							
College-share			0.351***	0.334***							
			(0.066)	(0.067)							
Manager type				-0.058***							
				(0.017)							
Manager sex				-0.047***							
				(0.017)							
Manager age				0.060***							
				(0.021)							
Manager education				0.003							
				(0.014)							
10-19 Employees	-0.920***	-0.895***	-0.908***	-0.878***	-0.919***			-0.802***	-0.802***	-0.802***	-0.802***
	(0.017)	(0.017)	(0.027)	(0.028)	(0.028)			(0.023)	(0.031)	(0.030)	(0.032)
20-49 Employees	-0.726***	-0.699***	-0.706***	-0.684***	-0.715***			-0.625***	-0.625***	-0.625***	-0.625***
	(0.017)	(0.016)	(0.026)	(0.027)	(0.027)			(0.022)	(0.030)	(0.030)	(0.031)
50-249 Employees	-0.412***	-0.392***	-0.403***	-0.388***	-0.405***			-0.364***	-0.342***	-0.342***	-0.341***
	(0.017)	(0.017)	(0.028)	(0.028)	(0.028)			(0.022)	(0.030)	(0.030)	(0.031)
Year dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry dummies	yes	yes	yes	yes	-	-	yes	yes	yes	yes	yes
Region dummies	yes	yes	yes	yes	-	-	yes	yes	yes	yes	yes
Year ∗ Industry dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	13,860	13,860	5,216	5,216	5,216	6,989	6,989	6,989	3,576	3,576	3,576
Number of firms	9,405	5,216	5,216	5,216	5,216	3,089	3,089	3,089	2,765	2,765	2,765

Source: RIL-AIDA dataset (years: 2005, 2007 and 2010)

*Robust standard errors in parenthesis; ***, ** and * denote respectively, 1%, 5% and 10% significance level. The reference group for 'blue-' and 'white-collars share' is managers share; for the age distribution is over-50 years old share; for education distribution is middle-school share; for the size dummies is more than 250 employees. Region dummies collect 20 dummies, one for each administrative region in Italy; industry dummies collects 199 dummies, one for each 3-digit Ateco 2002 industry; year * industry dummies are the interactions between year and industry dummies, as previously defined. 'Manager type' is a dummy which takes on 0 value if the manager is the owner and 1 if he/she is an internal/external manager; 'Manager sex' is a dummy that equals to 1 if the manager is a female; 'Manager age' is a dummy which equals 1 if the manager is over-40; 'Manager education' is a dummy that takes on a value of 1 if the manager has a college degree or more.*

Table 5: **Results; extensions: types of part-time; estimation method: OLS**

Dependent variable: $\widehat{TFP}_{it}$ *- ACF-FE estimates*

Horizontal part-time share	-0.148***	(0.033)
Vertical part-time share	-0.013	(0.101)
Mixed part-time share	-0.197**	(0.081)
Number of firm-year observations: 13,860		
Number of firms: 9,405		

Source: RIL-AIDA dataset (years: 2005, 2007 and 2010)
All the estimations include the same set of controls in Specification (2) of Table 4. See footnote of Table 4.

Table 6: **Results; extensions: reasons; estimation method: OLS**

Dependent variable: $\widehat{TFP}_{it}$ *- ACF-FE estimates*

	Worker's request	**Firm's willing**
Part-time share	-0.254***	-0.134***
	(0.065)	(0.050)
Number of firm-year observations	6,411	2,828

Source: RIL-AIDA dataset (years: 2005, 2007 and 2010)
The estimates are performed on sub-samples of firms-year observations using part-time work (9,434). In order to split the sample on the basis of the reasons of part-time use (i.e either worker's or firm's willing) we have to remove those observations (amounting to 195) for which the item 'other reason' have been chosen, since we do not know whether they belong to the first or second group. All the estimations include the same set of controls in Specification (2) of Table 4. For the rest, see footnote of Table 4.

Table 7: **Results; extensions: clauses; estimation method: OLS**

Dependent variable: $\widehat{TFP}_{it}$ *- ACF-FE estimates*

	Flexible and/or Elastic Clauses	**No clauses**
Part-time share	-0.108**	-0.191***
	(0.051)	(0.058)
Number of firm-year observations	3,467	5,967
Only years 2005 and 2007		
Part-time share	-0.055	-0.103*
	(0.078)	(0.062)
Number of firm-year observations	2,014	3,123
Only year 2010		
Part-time share	-0.170**	-0.271***
	(0.068)	(0.089)
Number of firm-year observations	1,453	2,844

Source: RIL-AIDA dataset (years: 2005, 2007 and 2010)
The estimates are performed on sub-samples of firms-year observations using part-time work (9,434). All the estimations include the same set of controls in Specification (2) of Table 4. For the rest, see footnote of Table 4.

Table 8: **Results; extensions: industry differentials; estimation method: OLS**

Dependent variable: $\widehat{TFP}_{it}$ *- ACF-FE estimates*

Industry	**Part-time share**	**Observations**	**Mean**	**Std. Dev.**
Manufacturing	-0.122**	6,897	0.062	0.089
	(0.050)			
Construction	-0.228*	2,002	0.049	0.075
	(0.118)			
Trade	-0.215**	1,467	0.106	0.140
	(0.091)			
of which: Retail	0.006	346	0.173	0.189
	(0.141)			
Transportation and communication	-0.467**	1,111	0.055	0.094
	(0.186)			
Services	-0.203***	2,383	0.177	0.245
	(0.048)			
				Number of firm-year observations: 13,860
				Number of firms: 9,405

Source: RIL-AIDA dataset (years: 2005, 2007 and 2010)
All the estimations include the same set of controls used in Specification (2) of Table 4. For the rest, see footnote of Table 4.

Appendices

A First step: estimating the TFP

To begin with, we assume that the equation relating output to inputs and TFP is a production function of the Cobb-Douglas type:

$$Y_{it} = A_{it} L_{it}^{\beta_l} K_{it}^{\beta_k} \tag{6}$$

where A_{it}, the TFP, is modeled as:

$$A_{it} = exp\{\alpha + \nu_t + \mu_j + \sigma_r + \omega_{it} + \epsilon_{it}\} \tag{7}$$

where α is the average productivity of the firms; ν_t, μ_j and σ_r are respectively time-, industry- and region-specific deviations from that mean; ω_{it} is the time- and firm-specific (i.e. idiosyncratic) deviation from that mean; whereas ϵ_{it} is a measurement error by assumption not correlated with inputs.

Moreover, we assume that labor and capital are not perfectly flexible inputs. Intuitively, this means that the amounts of labor and capital to be used in the production process at t are actually decided by the firm at $t-1$. This assumption is consistent with the fact that, on the one hand, new capital takes time to be ordered, delivered, installed and put into operation and that, on the other hand, it takes time to fire and/or hire workers. In the rest of the discussion, we will refer to this as the 'timing assumption'.

In practice, the production function that we estimate is obtained by using (7) and by taking logs in (6):

$$y_{it} = \alpha + \beta_l l_{it} + \beta_k k_{it} + \nu_t + \mu_j + \sigma_r + \omega_{it} + \epsilon_{it} \tag{8}$$

where lowercase letters indicate natural logarithms.

A crucial issue in estimating production functions lies in the simultaneity of inputs. Labor and capital are likely to be correlated with the productivity of the firm (i.e. with A_{it}): if the firm faces a positive productivity shock, it may decide to expand its output by increasing the usage of labor and/or capital.[24] Notice that, since ν_t, μ_j and σ_r are easily accounted for by inserting time, industry and region dummies, the real concern is on ω_{it} which is unobservable to the econometrician and idiosyncratic to the firm. Hence, the rest of the discussion is focused on ω_{it} rather than on the whole expression for (the log of) A_{it}

[24] We are implicitly assuming that the firm knows (at least partially) its productivity.

and, for the sake of notation, we write the production function as:

$$y_{it} = \alpha + \beta_l l_{it} + \beta_k k_{it} + \omega_{it} + \epsilon_{it} \tag{9}$$

where y_{it}, l_{it} and k_{it} are from now on the time-, industry- and region-demeaned output, labor and capital.

The simultaneity problem makes OLS estimates of (9) and, consequently, of the TFP[25], inconsistent. According to the assumptions that are made on the structure of ω_{it}, several methods can be used to deal with the simultaneity of inputs. Whether one method is better than another depends on what we think is the most realistic set of assumptions made about ω_{it}.

If we are willing to believe that ω_{it} is constant over time (i.e. $\omega_{it} = \omega_i$), exploiting the time dimension of our data, we are able to get rid of the simultaneity problem (i.e. of ω_i), by running an OLS regression on the within-group transformation of (9):

$$\widetilde{y}_{it} = \beta_l \widetilde{l}_{it} + \beta_k \widetilde{k}_{it} + \widetilde{\epsilon}_{it} \tag{11}$$

where the tilde operator indicates the within-group transformation: $\tilde{x}_{it} = x_{it} - \frac{1}{T}\sum_{t=1}^{T} x_{it}$.[26]

Since the assumption that ω_{it} is constant over time is rather restrictive, other methods have been developed that try to solve the simultaneity issue while allowing ω_{it} to evolve over time according to a more flexible process. In the context of the control function approach, Olley and Pakes [1996], Levinsohn and Petrin [2003] and Ackerberg et al. [2006] are the most notable examples. Since the method by Ackerberg et al. [2006] is the one that we extend, we have decided to describe only it here (for a detailed discussion on the OP and LP methods, see Van Beveren [2012] and Del Gatto et al. [2011]).

In the ACF framework, ω_{it} evolves over time according to a first-order Markov process, its realization at time t is observed by the firm at time t (i.e. contemporaneously) and it is at least partially anticipated by the firms. Since ω_{it} is assumed to follow a first-order Markov process, it is possible to write:

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

[25] According to (2), the (natural) logarithm of the total factor productivity for firm i at time t is computed as:

$$lnA_{it} \equiv TFP_{it} = y_{it} - \widehat{\beta}_l l_{it} - \widehat{\beta}_k k_{it} \tag{10}$$

where $\widehat{\beta}_l$ and $\widehat{\beta}_k$ are the estimated production function coefficients.

[26] This procedure is known as fixed-effects (FE) or within-group regression. Notice that in this case μ_j and σ_r are already removed by the within-group transformation, since they are time invariant.

where I_{it-1} is the information set of firm i at time $t-1$; $g(\cdot)$ is a completely general function and represents the predictable component of ω_{it}; and ξ_{it} is the innovation in the productivity, which, by construction, is unpredictable by the firm, i.e. $E[\xi_{it}|I_{it-1}] = 0$. Notice that the assumption that ω_{it} follows a first-order Markov process, relates both to the stochastic process regulating ω_{it} and to the firms' information set. Basically, firms observe ω_{it} at t and form expectations on ω_{it} using $g(\cdot)$ at $t-1$.

The intermediate inputs, m_{it}, are assumed to be perfectly flexible: the choice of their amount to be used at t is made at t. Moreover, they are assumed not to have any dynamic implication: m_{it} does not depend on m_{it-1}.[27] Moreover, it is assumed that the demand for intermediate inputs is a function of labor, capital and firm productivity and that f is strictly increasing in ω_{it}:

$$m_{it} = f(l_{it}, k_{it}, \overset{+}{\omega}_{it}) \tag{12}$$

Intuitively, this amounts to require that the bigger the productivity, the larger the demand for intermediate inputs. If this (strict) monotonicity condition on f holds, it can be inverted out in order to deliver an expression of ω_{it} as a function of l_{it}, k_{it} and m_{it}, which are indeed observables:

$$\omega_{it} = f^{-1}(l_{it}, k_{it}, m_{it}) \tag{13}$$

This expression for ω_{it} can then be substituted into (9) to bring:

$$y_{it} = \alpha + \beta l_{it} + \beta k_{it} + f^{-1}(l_{it}, k_{it}, m_{it}) + \epsilon_{it} \tag{14}$$

At this point, ACF proprose a two-step strategy in order to recover estimates of β_l and β_k. In the first step, y_{it} is nonparametrically regressed against a function in l_{it}, k_{it} and m_{it}, which we call $\Phi(l_{it}, k_{it}, m_{it})$.[28] From this regression, we can identify the composite term:

$$\widehat{\Phi}_{it} = \widehat{\alpha + \beta_l l_{it} + \beta_k k_{it} + \omega_{it}}$$

Given guesses of β_l and β_k, i.e. β_l^* and β_k^*, it is then possible to recover implied ω_{it}, i.e. $\hat{\omega}_{it}(\beta_l^*, \beta_k^*)$[29], as:

$$\hat{\omega}_{it}(\beta_l^*, \beta_k^*) = \widehat{\Phi}_{it} - \beta_l^* l_{it} - \beta_k^* k_{it}$$

Recalling that ω_{it} is assumed to follow a first-order Markov process, i.e. $\omega_{it} = g(\omega_{it-1}) + \xi_{it}$, and given our implied $\hat{\omega}_{it}(\beta_l^*, \beta_k^*)$, it is possible to compute implied innovations $\hat{\xi}_{it}(\beta_l^*, \beta_k^*,)$ as

[27] On the contrary, capital and labor are not restricted to be non-dynamic. Adjustment costs in labor and capital are therefore admitted (e.g. hiring/firing costs and capital disposal costs).

[28] In our empirical analysis, we approximate $\Phi(\cdot)$ with a second-order polynomial in l_{it}, k_{it} and m_{it}.

[29] Notice that these implied $\omega_{it}'s$ also comprise the constant term α.

the residuals from a nonparametric regression of implied $\hat{\omega}_{it}(\beta_l^*, \beta_k^*)$ on implied $\hat{\omega}_{it-1}(\beta_l^*, \beta_k^*)$.[30] In the second step of this procedure, the sample analogues of the moment conditions imposed by our model[31] are evaluated:

$$\begin{aligned} \frac{1}{N}\frac{1}{T}\sum_i\sum_t \hat{\xi}_{it}(\beta_l^*, \beta_k^*)k_{it} = 0 \\ \frac{1}{N}\frac{1}{T}\sum_i\sum_t \hat{\xi}_{it}(\beta_l^*, \beta_k^*)l_{it} = 0 \end{aligned} \tag{15}$$

The search over β_l^* and β_k^* continues until $\hat{\beta}_l$ and $\hat{\beta}_k$ are found that satisfies (15). These are the ACF estimators of β_l and β_k.

Though we are confident that the ACF method represents a substantial improvement in dealing with the simultaneity problem with respect to simple FE, we argue that explicitly allowing and accounting for a time-invariant component in the structure of firm productivity, besides the time-varying one and still in the context of the ACF method, would represent a further enhancement at a relatively low cost. In a nutshell, ACF propose to proxy firm productivity, which is unobservable, through intermediate inputs demand. Very powerful this proxy though it may be, still some part of the firm productivity is likely to be left unexplained. In this perspective, removing the time-invariant part of the productivity, would definitely increase the chance for the proxy to work well. Following Vandenberghe et al. [2013], we argue that only the first stage of the ACF procedure needs to be modified in order to explicitly account for firm fixed-effects.

In this framework, the total factor productivity is modeled as:

$$\omega_{it} = \eta_i + \omega_{it}^* \tag{16}$$

According to (16), the firm productivity is composed by the sum of a time-invariant (η_i) and a time-varying (ω_{it}^*) component. On the one hand, η_i can be though of as including firm features such as the managerial quality, the culture of the firm and its international profile, which can be assumed to be fixed over time; whereas the time-varying component ω_{it}^* can be thought of as an idiosyncratic productivity shock hitting the firm at t. Note that we still assume that ω_{it}^* follows a first-order Markov process and that it is partially anticipated by firms. We then assume that the demand for intermediate inputs is given by:

$$m_{it} = f(l_{it}, k_{it}, \omega_{it}^*) \tag{17}$$

[30] In our empirical analysis, we approximate $g(\cdot)$ with a third-order polynomial in $\hat{\omega}_{it-1}(\beta_l^*, \beta_k^*)$.

[31] The moment conditions imposed by our model, stemming from the assumption that capital and labor are not perfectly flexible inputs, are: $E[\xi_{it}k_{it}] = 0$ and $E[\xi_{it}l_{it}] = 0$.

so that it solely depends on the amount of labor and capital to be used in t and the productivity shock observed at t. We exclude that the demand of intermediate inputs depends on η_i; this assumption rules out that factors such as management quality, culture and internationalization of the firm contribute in determining the demand of intermediate goods to be used in the production process. This does not seem an implausible assumption, since it is reasonable to think that the demand of intermediate inputs, which are by assumption perfectly flexible and non-dynamic, depends only on time-varying components. Moreover, we also preserve the assumption that f is invertible in ω^*_{it}. This set of assumptions imply that equation (14) is modified as follows:

$$y_{it} = \alpha + \beta l_{it} + \beta k_{it} + \eta_i + f^{-1}(l_{it}, k_{it}, m_{it}) + \epsilon_{it} \tag{18}$$

As before, by setting $\Phi(l_{it}, k_{it}, m_{it}) \equiv \alpha + \beta l_{it} + \beta k_{it} + f^{-1}(l_{it}, k_{it}, m_{it})$, we can write (18) as:

$$y_{it} = \Phi(l_{it}, k_{it}, m_{it}) + \eta_i + \epsilon_{it} \tag{19}$$

At this point we are able to remove η_i from (19) applying (nonparametric) FE estimation.[32] From FE estimation of (19), we are able to obtain a consistent estimate of $\Phi(\cdot)$, i.e. $\hat{\Phi}(\cdot)$, so that it is possible to proceed to the (unchanged with respect to the ACF method) second stage of the estimation from: $\widehat{\Phi}_{it} = \widehat{\alpha + \beta_l l_{it} + \beta_k k_{it} + \omega^*_{it}}$.

[32]In the empirical analysis, we again approximate $\Phi(\cdot)$ with a second-order polynomial in l_{it}, k_{it} and m_{it}. Notice that, as in the simple FE case, μ_j and σ_r are already removed by the nonparametric FE estimation, since they are time invariant.

B The AIDA dataset

The AIDA dataset contains comprehensive information on balance sheet data for all (non-financial and non-agricultural) incorporated firms in Italy. Among the variables included in the AIDA dataset we mention: the region of the firm, its industry (defined according to the Ateco 2002 classification), revenues, value added, net profit, book value of physical capital, total wage bill and raw-materials expenditure.

In our empirical analysis, output (y_{it}) is measured by the value added. Labor (l_{it}) is measured by the amount of personnel costs, including the wage bill and some fringe benefits. Even though the AIDA dataset provides information on the number of employees, we prefer to use the 'personnel costs' item for measuring the labor input because the first variable has a sizeable amount of missing values (more that 30% of the original sample). Moreover, it allows to measure labor input more accurately, since it, at least to a certain extent, keeps into account the difference in working hours between full-timers and part-timers and overcomes problems stemming from difference in the quality of the workforce. Capital (k_{it}) is measured by the amount of tangible fixed assets. In particular, we compute capital through a version of the Permanent Inventory Method that applies a constant depreciation rate (0.065) to tangible fixed assets. Finally, the intermediate input demand (to be used in the ACF and ACF-FE methods) is measured by the 'raw materials' item in the balance sheet.

The dataset used in our analysis is the result of some cleanings with respect to the original version. We remove firms belonging to the mining industries (they are a few) and to sectors in which the public intervention is substantial, such as production and distribution of electricity, gas and water and garbage disposal. We restrict the attention to firms classified as 'active' and to firms with average revenues greater than 50,000 Euros per year. In order to be able to estimate the production functions, we are forced to remove observations for which value added, capital, labor costs and materials expenditures have missing, negative or zero values. Finally, in order to perform LP, ACF and ACF-FE estimations we have to restrict our attention to firms for which we have at least two *consecutive* years of observations.

The final dataset is made of 2,406,612 firm-year observations for 440,953 firms. While for 8.08% of firms we have the complete observation window (11 years), for half of them we have more that 5 years of observations. Table 9 shows the distribution of the AIDA dataset across the 40 sectors (2-digit Ateco 2002 classification) for which we estimate a separate production function. As shown in Table 9, about one third of the observations belongs to the manufacturing industry. Trade and services sectors cover respectively about 29% and 21% of the observations; while the remaining observations are split between construction (14.1%) and transportation and communication industry (4.18%).

Table 9: **AIDA dataset: Distribution of observations by sector of economic activity (2-digit Ateco 2002)**

Sector of economic activity	**Frequence**	**Percentage**
Manufacturing	*783,129*	*32.54*
Food and beverage	59,613	2.48
Tobacco	146	0.01
Textile	42,434	1.76
Clothing	30,543	1.27
Leather and leather goods	28,837	1.20
Wood and wood products (excluding furniture)	23,615	0.98
Paper and paper product	14,900	0.62
Printing and publishing	37,295	1.55
Coke and petroleum products	2,016	0.08
Chemical products	27,386	1.14
Rubber and plastics	37,835	1.57
Non-ferrous production	44,267	1.84
Ferrous production	15,307	0.64
Ferrous products (excluding machinery)	150,075	6.24
Machinery products	108,722	4.52
Office machinery and computers	6,240	0.26
Electrical machinery	33,566	1.39
Radio, TV and TLC equipment	12,614	0.52
Medical equipment and measurement instruments	22,407	0.93
Motor vehicles	9,942	0.41
Other transportation equipment	10,824	0.45
Furniture and other manufacturing industries	58,161	2.42
Recycling	6,384	0.27
Construction	*339,776*	*14.12*
Construction	339,776	14.12
Trade	*688,506*	*28.61*
Trade and maintenance of Motor vehicles	95,059	3.95
Wholesale (excluding mothor vehicles)	373,492	15.52
Retail (excluding mothor vehicles)	219,955	9.14
Transportation and Communications	*100,544*	*4.18*
Land transportations / transportations by pipeline	53,030	2.20
Maritime transportations	1,973	0.08
Air transport	578	0.02
Auxiliary transportations activities	40,775	1.69
Post and telecommunications	4,188	0.17
Services	*494,657*	*20.55*
Hotels and restaurants	121,228	5.04
Real estate	67,876	2.82
Rental services	10,723	0.45
Computer and related activities	83,998	3.49
R&D	3,959	0.16
Business services	155,951	6.48
Recreational, cultural and sport activities	36,411	1.51
Household services	14,511	0.60
Total	2,406,612	100

Source: AIDA dataset (period: 2000-2010)

C The TFP estimates

Table 10 shows the correlation matrix of the different TFP estimates, while Table 11 shows their summary statistics. The different TFP estimates are positively and highly correlated among each other: correlation coefficients range between 0.826 and 0.968 (see Van Beveren [2012] for a similar finding). ACF and ACF-FE estimates, the ones intended to be able the most in dealing with the simultaneity issue, are very similar with respect to the OLS estimates (correlation coefficients are 0.968 and 0.948 respectively). As expected, given the high correlations, their summary statistics are quite similar. The mean of the TFP estimates ranges between 3.061, for the OLS method, and 5.506, for the FE one. This suggests that the simultaneity issue, though being conceptually relevant, looses part of its importance in practice. Still, the relevance of the simultaneity problem and, consequently, the empirical validity of the methods trying to deal with it should be assessed in view of the conclusions that they lead to in analyzing the impact of interest (see Appendix D, Table 12 for this).

Table 10: **AIDA dataset: Correlation matrix of different estimates of the TFP (OLS, FE, LP, ACF, ACF-FE)**

TFP estimates	OLS	FE	LP	ACF	ACF-FE
OLS	1.000				
FE	0.857	1.000			
LP	0.863	0.845	1.000		
ACF	0.968	0.898	0.871	1.000	
ACF-FE	0.948	0.928	0.826	0.958	1.000
Number of firm-year observations: 2,406,612					
Number of firms: 440,953					

Source: AIDA dataset (period: 2000-2010)

Table 11: **AIDA dataset: Summary statistics of different estimates of the TFP (OLS, FE, LP, ACF, ACF-FE)**

TFP estimates	**Mean**	**Std. Dev.**	**1st Q.**	**Median**	**3rd Q.**
OLS	3.061	1.106	2.229	3.118	3.662
FE	5.506	1.241	4.608	5.435	6.340
LP	5.205	1.176	4.371	5.070	5.934
ACF	3.694	1.143	2.860	3.762	4.358
ACF-FE	3.924	1.356	2.851	4.071	4.741
Number of firm-year observations: 2,406,612					
Number of firms: 440,953					

Source: AIDA dataset (period: 2000-2010)

D Robustness checks

As a robustness check we perform OLS estimation restricting the attention to the pre-crisis period (i.e. 2005 and 2007). Results confirm that the part-time effect on TFP is significantly (at 5% level) negative also for the pre-crisis period and not substantially different from the general effect (-0.099 *versus* -0.146).

Table 12 shows results for the impact of part-time on the different sets of TFP estimates (i.e. OLS, FE, LP, ACF and ACF-FE). Not surprisingly, considering the generally high correlations among the different TFP estimates, we find that the predicted impact of part-time on TFP is negative, whatever the first-step estimation method is. However, the magnitude of the impact somewhat differs across methods, ranging between -0.233, when LP estimates of the TFP are considered, and -0.091, when TFP is estimated through simple OLS. Interestingly, our reference method (i.e. the ACF-FE), delivers quite similar estimates of the impact of interest with respect to those stemming from the simple OLS estimation of the TFP. On the contrary, FE and LP estimations, most likely to suffer from well-know problem of downward bias, for the FE case, and collinearity, for the LP case, deliver more different estimates with respect to the ACF-FE method.

Table 12: **Results; robustness checks: OLS, FE, LP, ACF TFP estimates of the TFP as dependent variables; estimation method: OLS**

TFP estimation method	OLS	FE	LP	ACF	ACF-FE
Part-time share	-0.091***	-0.233***	-0.217***	-0.125***	-0.146***
	(0.030)	(0.034)	(0.032)	(0.030)	(0.031)
Absolute difference from ACF-FE estimate	0.055	0.087	0.071	0.022	-
Number of firm-year observations: 13,860					
Number of firms: 9,405					

Source: RIL-AIDA dataset (years: 2005, 2007 and 2010)

The estimation includes the same set of controls used in Specification (2) of Table 4. For the rest, see footnote of Table 4.

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