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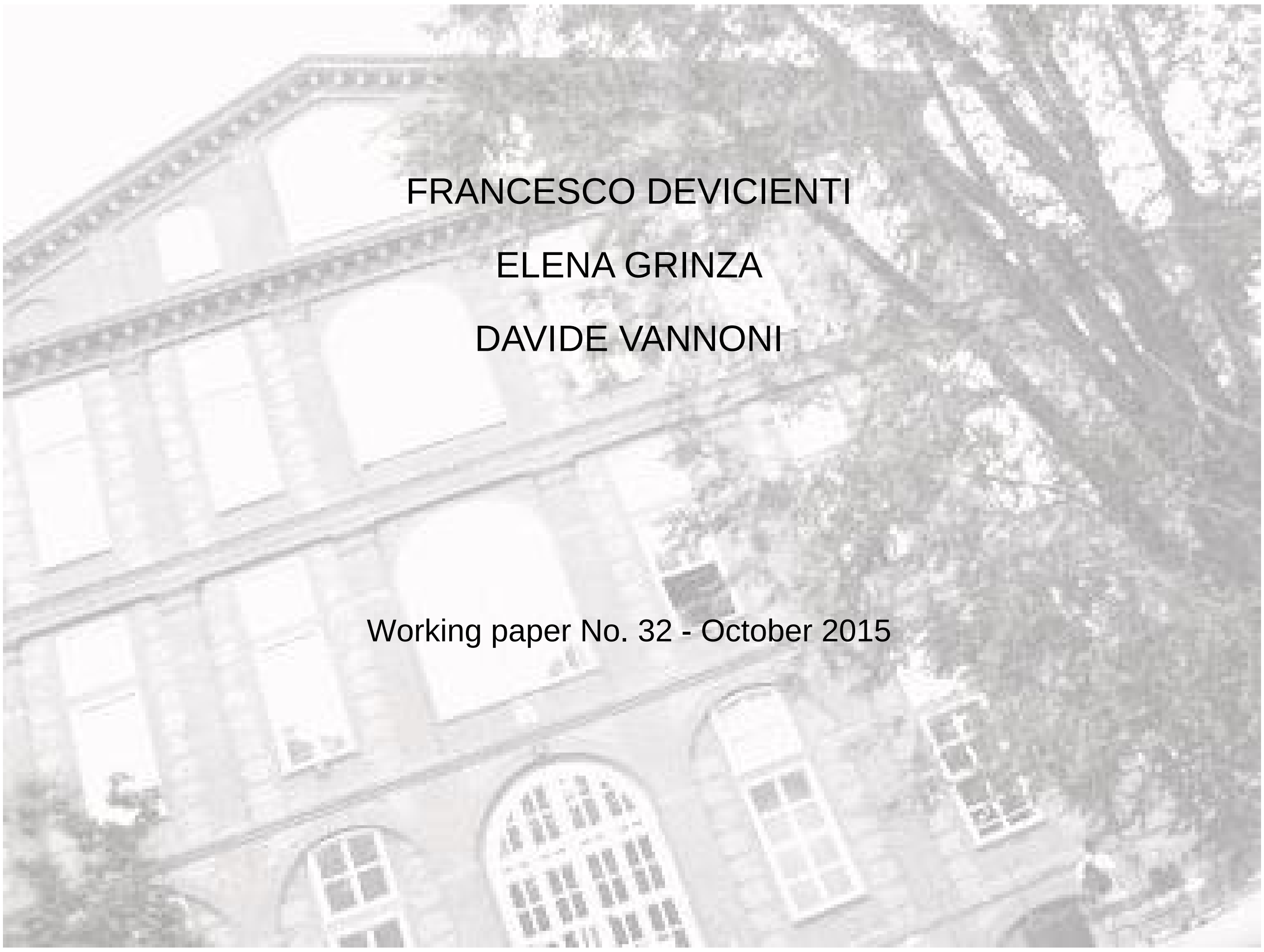

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The Impact of Part-Time Work on Firm Total Factor Productivity: Evidence from Italy

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Abstract

In this paper, we explore the impact of part-time work on firm productivity. Using a large panel data set of Italian corporations' balance sheets for the period 2000-2010, we first estimate the total factor productivity (TFP) of each firm for each year. We use different approaches aimed at solving input simultaneity, including a version of Ackerberg et al.'s (2006) control function approach, which accounts for firm fixed effects. We then match the TFP estimates with rich information on the firms' use of part-time work obtained from survey data and estimate the impact of part-time work on TFP at the firm level. We find that an increase of 1 standard deviation in the part-time share reduces TFP by 2.03%. The results suggest that this harmful effect stems from horizontal rather than vertical part-time arrangements. We also find that firms declaring that they use part-time work to accommodate workers' requests suffer the most. Moreover, we show that the so-called 'flexible' and 'elastic' clauses are successful in reducing the negative impact associated with part-time work.

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

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1. Introduction

Since the mid-1970s, part-time work has become increasingly common, and now it represents a pervasive feature of work arrangements. According to Eurostat, about one-fifth of the total employees in Europe were 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 question of whether it is beneficial or not for firm productivity is of great relevance for both managers and policy makers. Nonetheless, only a limited number of studies have addressed this issue, while the bulk of the literature on part-time work has focused on the supply side, also in the perspective of its alleged positive role in increasing female participation in the labor market.

To our knowledge, only three papers have tried to assess empirically the impact of part-time work on (labor) productivity. Garnero et al. (2014), using a longitudinal matched employer-employee data set 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 similar panel of Belgian firms 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 than 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 2 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 specific 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, that is, the labor productivity of part-timers with respect to full-timers, and with respect to the productivity of the firm as a whole, that is, total factor productivity.

If a non-constant relationship exists 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 due to lower incentives to invest in human capital accumulation.

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 in which the activities are concentrated in only a few hours per day or firms in which the operating hours exceed the full-time working week may benefit from part-time work (Owen, 1978).

In this paper, we focus on the impact of part-time work on a firm's TFP. Our empirical analysis is based on an Italian firm-level data set - the Employer and Employee Survey (RIL) - conducted by the Institute for the Development of Workers' Vocational Training (ISFOL) in 2005, 2007, and 2010. The RIL data are uniquely rich in terms of information related to the use of part-time work in the firm, which constitutes the major reason for using this source in our analysis. The available information to estimate a firm's TFP is, instead, more limited; moreover, the RIL has only a short (three-year) panel component. However, firm-level TFP estimates can be obtained from AIDA, a much larger panel data set distributed by the Bureau Van Dijk, which contains the official balance sheets of (almost) all private sector Italian corporations for the period 2000-2010. Fortunately, AIDA can be matched to the RIL using a firm's tax number (*codice fiscale*).

Our empirical analysis is conducted in two steps. In the first step, we recover TFP estimates from AIDA, taking advantage of its large size (to increase the efficiency of our estimates) and its longer panel dimension (which allows us to control for firm fixed effects in the first-stage TFP estimates). We define TFP 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 of the semiparametric approach developed by Ackerberg et al. (2006). This method, proposed by Vandenberghe et al. (2013), accounts for firm-specific fixed effects in the estimation of TFP. Then, using the firm tax number, we match the TFP estimates obtained from the AIDA data set with the RIL data set. In the second step of our procedure, we finally analyze the impact of part-time work on TFP for the matched RIL firms.

The main result is that part-time work is detrimental to firm productivity: a 1 standard deviation increase in the part-time share (0.14) is estimated to decrease TFP by 2.03%. 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 between part-timers and full-timers, we interpret our results in terms of the communication, coordination, and transaction costs that part-time work imposes on the firm, consequently lowering its general efficiency. According to this interpretation, the effect of part-time work concerns organizational efficiency, as captured by the firm's TFP.

Thanks to the rich information on part-time work provided by the RIL data set, we are also able to investigate some of its dimensions, which, at least to our knowledge, have not been explored previously. In particular, we are able to distinguish between three types of part-time work: horizontal, vertical, and mixed. Horizontal part-time work, the most common kind, involves a reduction of the *daily* working time (e.g. working 5 hours per working day, instead of 8 hours per day as full-timers generally do). Vertical part-time work, 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 work combines horizontal and vertical characteristics. Our findings show that the negative effect of part-time work is exerted by the horizontal (and mixed) part-time work, whereas vertical part-time work is found to have virtually no effect on firm productivity. This result is consistent with the presence of *daily* communication and coordination costs.

Moreover, we have information on whether part-time work is adopted to accommodate workers' requests for 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 work has a stronger (negative) impact when the firm uses it to accommodate workers' requests.

Finally, information is available on whether the firm uses part-time work jointly with 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 these clauses make part-time work less harmful, suggesting that they may represent a good compromise between firms' and workers' needs and may eventually lead more firms to hire workers who ask for contracts on a part-time basis.

The rest of the paper is structured as follows: in Section 2, we undertake 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 data sets used in the analysis; Section 6 presents and discusses our results; and Section 7 concludes.

2. Literature Review

The academic literature on part-time work has traditionally been concerned with the supply side of the market. Using individual-level data, it has focused on investigating issues such as the determinants of part-time labor supply, its role in granting individuals (especially women) a satisfactory work-life balance or the part-time *versus* full-time wage gap.[3]

When dealing with the demand side, both the theoretical and the empirical literature on part-time work have been more concerned with the determinants of firms' use of part-time work than with 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 can affect productivity. In general, it is possible to distinguish among two macro categories: theories that concentrate on the impact of part-time work on the individual productivity of labor and theories that emphasize the impact of part-time work on firms' 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 that they work depends on the relationship between the labor productivity and the number of hours worked during the day. If the 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. a positive sloped curve or an 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 and picks up only slowly during the day, argues that part-time workers have 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 a certain 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 that 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 (2009), another strand of the literature suggests that part-timers have fewer incentives to invest 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).

[3]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 determinants of their decision to work part-time; Gregory and Connolly (2008), for an assessment of the role of part-time work in granting work-life balance for women.

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 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 in which workers can be easily substituted for each other (e.g. along the assembly line), it could be relevant to jobs in which task-specific skills matter (e.g. clerical work). In this case, part-time work may also create information inefficiencies and communication costs. On the other hand, papers related to the demand for part-time labor (e.g. Owen, 1978) have emphasized the allocation efficiency that part-time work may produce. In particular, firms experiencing workload peaks during certain hours or days and firms in which the 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 those kinds 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 work 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 the differences in hourly wages, finding contrasting results. For example, Ermisch and Wright (1993), for British women, and Baffoe-Bonnie (2004), for the USA, find a significant wage differential between part-timers and full-timers, with part-timers being paid less. However, Hirsch (2005) finds no significant wage gap in his USA sample, after controlling for individual and job characteristics. It is worth emphasizing that the existence of any productivity differentials predicated on the basis of these studies is only valid to the extent that labor productivity is reflected in hourly wages, an unwarranted assumption in imperfect labor markets.

Using firm-level data, Arvanitis (2005) is the first to assess the relationship between part-time work and a more 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 work, he finds that part-time labor is negatively related to labor productivity in a sample of

Swiss firms.

Besides Arvanitis (2005), three papers assess labor productivity differentials between part-timers and full-timers through the use of firm-level measures of labor productivity and in the context of production functions.

On the one hand, Garnero et al. (2014) use a large matched employer-employee data set for Belgium for the period 1999-2010 with the aim of exploring the relationship between wage/productivity differentials between part-timers and full-timers, to evaluate whether there are any employer rents associated with the use of part-time work. Concerning 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[4] part-timers, whereas the other categories, namely 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[5] 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 contributions of different groups of workers (e.g. full-timers *versus* part-timers) to average labor productivity and to average wages allow the authors to investigate whether some of these groups 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 data set from the one used by Garnero et al., 2014), find that part-timers 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.[6] 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 with 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 data set 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,

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

[5]'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).

[6]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%.

a 10% increase in the part-time share is associated with an increase in the average labor productivity of 4.8%.

Since the paper by Künn-Nelen et al. (2013) concentrates on a very particular industry, our paper ends up being comparable with those of Garnero et al. (2014) and Specchia and Vandenberghe (2013), who, though analyzing the same country in (almost) the same period, obtain contrasting results.

3. Empirical Model and Identification

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

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

where output (Y_{it}) is modeled as a function of labor (L_{it}) and capital (K_{it}) and A_{it} is the total factor productivity. 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 the output that is not explained by the amount of labor and capital used, that is, 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 firm strategies such as R&D investments, exports, and FDIs to the labor policies carried out by the firm, for example the use of part-time work[7], PT_{it}:

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

Although it would be possible to examine the effect of part-time work on TFP by directly

[7]According to this framework, part-time labor enters the production function through the TFP. Alternatively, one may assume that part-time workers and full time workers enters additively in a labor aggregate, but with a potentially different *labor* productivity, as in Hellerstein et al. (1999). Disentangling the effects of part-time work on TFP vs on labor productivity is difficult. In fact, when the production function is specified as a Cobb-Douglas and is log-linearized, as in Garnero et al. (2014), Specchia and Vandenberghe (2013) or Vandenberghe et al. (2013), the effect of (the share of) part-time workers can be alternatively interpreted as affecting the TFP or labor productivity. More general production functions might in principle allow for the identification of the two separate effects. However, in the absence of hard data on individual productivity, as opposed to firm-level productivity, this task is rather demanding and is not currently pursued in the literature.

estimating (1), due to data-related motivations that will be illustrated later, we prefer to proceed in two steps. In the first step, we retrieve the TFP estimates according to (2). In the second step, we analyze the impact of part-time work on TFP by estimating (3).

In the first step, we assume that the production function in (1) is a log-transformed Cobb-Douglas function. A relevant issue in the estimation of production functions is the potential correlation between the inputs and the unobserved TFP. For instance, a firm hit by a positive productivity shock is likely to increase its use of labor and capital inputs. This issue, commonly known as the 'simultaneity problem', makes OLS estimates inconsistent. To solve this problem, several solutions have been proposed. If one is willing to assume that firm productivity is constant over time, fixed-effects (FE) estimation solves it. However, this assumption is controversial. 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 proxying for unobserved productivity through the firm's investment demand. Levinsohn and Petrin (2003) (LP) instead suggest using 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 and hence more able to capture them. 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 obtained in the second step of the estimation procedure. Following Vandenberghe et al. (2013), we adopt a version of the ACF method that explicitly accounts for firm-specific fixed effects (ACF-FE). We argue that this procedure is more effective than ACF in delivering consistent estimates because, by removing the time-invariant unobserved heterogeneity, it increases the ability of the productivity proxy to capture the unobserved firm-specific productivity level. Appendix A provides a detailed discussion on the simultaneity problem and the methods developed to solve it.

In the empirical analysis, we estimate a separate production function for each industry (as defined by the 2-digit Ateco 2002 classification) to account for the structural differences (e.g., in the production process or in industrial relation practices) among different sectors. In total, we estimate 40 different production functions. We perform OLS, FE, LP, ACF, and ACF-FE estimation.[8] All the estimations include year, region, industry, and year interacted by industry dummies (industry is defined according to the 3-digit Ateco 2002 classification). 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 we have

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

information on the number of employees, we prefer to use the 'personnel costs' item, because it allows us to measure labor input more accurately, since it takes into account, at least to a certain extent, the difference in working hours between full-timers and part-timers (which we do not observe) and overcomes the problems stemming from the differences in the quality of the workforce. Moreover, the differences in the *average* hours worked by part-time and full-time workers are accounted for by our estimation of separate production functions by industry. Capital (K_{it}) is measured by the amount of tangible fixed assets.[9] Finally, the intermediate input demand (to be used in the ACF and ACF-FE methods) is measured by the 'raw materials' item on the balance sheet. After estimating the production functions, we compute the corresponding TFP estimates according to (2). In view of the considerations made previously, the TFP estimates obtained from the ACF-FE estimation are elected as our reference measure of firm productivity. A robustness analysis using alternative TFP measures is conducted in the appendix.

In the second step, we explore the impact of part-time work on TFP. Specifically, we consider alternative specifications of the following regression model:

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

where: PT_{it} is the number of part-timers over the firm's total number of employees and is our regressor of interest; V_{it} is a vector collecting some variables included as controls (e.g. female share, non-EU workers 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 work. In particular, one may argue that some unobservable time-invariant and firm-specific characteristics, such as managerial ability, besides contributing to determining firm productivity, also influence the share of part-time work 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 workers' requests 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 to avoid firing them. The practical relevance of such concerns will be assessed by comparing the simple OLS estimates with those obtained with fixed-effects and instrumental variable (IV) regressions.

[9] In particular, capital is computed through a version of the Permanent Inventory Method that applies a constant depreciation rate (0.065) to tangible fixed assets.

4. The Italian Case

In all industrialized countries, including Italy, part-time work started to be used increasingly in the middle of the 1970s. As Kalleberg (2000) points out, the main determinants of its constant growth can be found in the increased uncertainty of the general economic conditions and in the (consequent) sharpened competition among firms, which eventually led 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 permanent), contributed to the growth of part-time work, intended as a way for firms to escape the costs and legal duties associated with these laws. Demographic changes in the composition of the labor force have played a fundamental role, too: the rises in married female workers and older workers, attracted by the flexibility characterizing part-time work, are the two most straightforward examples.

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

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

Data provided by the ISFOL[10] show that part-timers are over-represented in young age groups and that female part-timers are over-represented in the central age category, presumably because this is the age at which women have children. Although for women the incidence of part-time work is largest among the low-educated category, the contrary applies to males. While part-timers are generally segregated into low-skilled jobs, in the trade and services sectors they are over-represented in high-skilled occupations. Finally, part-timers are segregated into temporary contracts and into the trade and household services sectors.

According to the OECD, in 2010, about 40% of Italian part-timers declared themselves to be employed on a part-time basis against their will. Together with this involuntary part-time employment, a phenomenon exists that can also be referred to as 'involuntary part-time' employment to all intents and purposes. Many firms[11] use part-time work to accommodate workers' requests for shorter working hours and would prefer to employ their

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

[11] According to the 2010 RIL survey, they are about 60% of those using part-time arrangements.

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, highlights a substantial misalignment between the demand and the supply of part-time labor, which eventually leads to dissatisfaction among many workers and firms.

In Italy, part-time work received its first, 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 equal treatment between part-time and full-time workers, both in relation to the hourly pay and annual leave and in relation to other kinds of non-monetary benefits. According to the Italian legislation, the reduction of working hours can occur in three ways: the horizontal model, in which the employee works all the working days with a reduction in the daily working time; the vertical model, in which the employee works full-time, but only on some days of the week, month, or year; and the mixed model, which is a combination of the horizontal and the vertical part-time model. Part-time work contracts must 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 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 curtailing) the number of working hours in vertical part-time contracts. The procedures for the use of such clauses are provided by the law and by the sectoral labor collective agreements applied to the specific productive unit.

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 greater flexibility and discretion in the signing of part-time work contracts. Compared with the early regulations, the 2003 Biagi's Law and, less extensively, the 2007 legislative decree have granted greater flexibility in the working time arrangements and have reduced the restrictions on carrying out additional/overtime work and on stipulating flexible or elastic clauses. Moreover, they have left an active role to collective bargaining in integrating the legal regulation and concretely ruling part-time work. However, as we shall see later in the discussion, the legislative decree in 2007, though in general oriented toward increasing part-time work flexibility, significantly reduced firms' prerogative with respect to the signing of the elastic and flexible clauses introduced by Biagi's Law.

5. Data

To assess the impact of part-time work on TFP, we use the three available waves of the RIL survey, for 2005, 2007, and 2010. Each wave of the survey interviews over 23,000 private sector Italian firms, including both partnerships and corporations. Only a sub-sample of the included firms is followed over time, making the (complete) RIL data set partially panel. The data are uniquely rich concerning the composition of the workforce, including the fraction of part-timers and, among them, of horizontal, vertical, and mixed part-timers. Moreover, they provide information on the reasons for which the firm uses part-time work and on the use of flexible and elastic clauses. Finally, the data provide an extensive set of firm-level controls, including management characteristics and the age and education distribution of the workforce.

In the empirical analysis, we restrict our attention to firms with at least 10 employees. The rationale behind this restriction is twofold. First, since we are interested in the effect of part-time work on the organizational efficiency of firms, it is reasonable to consider firms with a minimal organizational structure. Second, the restriction is required to compute meaningfully the shares of employees in different work arrangements.

While the RIL data set provides accurate information on employees, the data on revenues, physical capital, and intermediate inputs are incomplete or completely absent. Hence, to obtain estimates of a firm's TFP, we have to resort to another data set. For this purpose, we use the AIDA data provided by the Bureau Van Dijk for the period 2000-2010. The data contain comprehensive information on the official balance sheets of (almost) all the Italian corporations operating in the private sector, except for the agricultural and financial industries. The data contain yearly values of such variables as revenues, value added, net profit, book value of physical capital, total wage bill and raw-materials expenditure, as well as information on the location of the firm and its industry affiliation (defined according to the Ateco 2002 classification). Using the AIDA data set to obtain the TFP estimates offers a number of advantages. Thanks to its width (about 2.5 million observations), it is still possible to gain precise estimates while estimating 40 different production functions. Moreover, the relatively long panel improves the performance of the methods that exploit the within-firm variation (i.e. all but OLS) to perform better. To minimize attenuation biases related to measurement error, we carry out an essential cleaning procedure, as is typically performed in the literature on the estimation of TFP from balance sheet data. Appendix B provides a detailed description of this procedure and reports some summary statistics of the AIDA data set.

Through the national tax number (*codice fiscale*), which uniquely identifies each firm in both data sets, it is possible to match the TFP estimates recovered from AIDA with the

RIL's firms. We will refer to the resulting data set as the 'RIL-AIDA' data set. Out of 22,696 firm-year potential matches, 14,889 are actually matched with the TFP estimate from the AIDA data set, resulting in a merge rate of about 66%. This result should be considered in view of the following facts. On the one hand, AIDA does not contain data for agricultural and financial firms, while RIL does. On the other hand, besides the basic cleaning procedure described in Appendix B, we are forced to remove from AIDA any observations with missing, negative, or zero values of the variables used in the production function. Moreover, to perform all the semiparametric methods described before, we need to restrict the attention to the AIDA firms with at least two *consecutive* years of observations.[12] Finally, we cannot exclude coding errors in the reported tax number from either data set, errors that we expect to be random.

The final version of the RIL-AIDA data set used in the second step is made up 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 largest, accounting for almost 50% of the observations. The services and trade sectors represent about 18% of the observations, while the rest of the sample 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 1 observation: this is due to the partially-panel nature of the RIL data set. About 26% of the firms are observed over 2 periods, while about 11% of them are observed over 3 periods.[13]

Table 2 presents some summary statistics of the RIL-AIDA data set. On average, firms' revenues are 33 million euros per year, but for 50% of the observations they are lower than 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), consistently with the Italian industrial structure in which small- and medium-sized firms represent the great majority of firms. On average, 31% of employees are female and 6% originate from non-EU countries, while 10.5% are employed on a temporary basis. About 59% of employees are blue-collar workers, 36% are white-collar workers, and about 5% fill a managerial position. The great majority of workers in the average firm have a low or medium level of education, while only 8.8% of them have a

[12] Indeed, when considering the merge between the corporations with at least 10 employees in the RIL panel with the original version of the AIDA data set, i.e. without any variable cleanings, the merge rate increases to 92.5%. Still, the match is not full because we are not able to remove agricultural and financial firms from the RIL panel (in the RIL data set we observe industry classification with many missing values).

[13] The limited panel dimension of the RIL data is the main reason why we have not adopted the one-step ACF-FE procedure in Vandenberghe et al. (2013). Implementing this method would force us to restrict our analysis to firms with at least two *consecutive* observations, thus dropping about 75% of observations in our sample. In the next section we also report estimates of the effect of part-time work on TFP based on fixed-effects models using the more restricted sample.

college degree; on average, half of the workforce is aged between 35 and 49 years.[14]

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, in line with the fact that part-time positions are mainly occupied by women. Horizontal part-time work is by far the most widespread type of part-time work used by firms: on average, 87% of part-timers have a horizontal part-time contract, while the corresponding figures for vertical and mixed part-timers are 7% and 6%, respectively. In particular, female horizontal 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 work is used by the great majority of firms: about 68% of them employ 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 adopt these clauses. Excluding firms using mixed part-time work, it is possible to notice that the incidence of clauses varies according to the type of part-time work: 34% of firms using horizontal part-time work apply flexible clauses, while 39% of firms using vertical part-time work apply elastic clauses.[15] The bottom panel of Table 3 summarizes the answers given by firms employing some part-timers regarding the main reason for their use of part-time work. The vast majority of them (68%) declare that they use part-time work to accommodate workers' requests for shorter working time.[16] The remaining 32% is split between those that use it willingly (30%) and those that give answers that differ from the proposed alternatives (2%). Among the firms that declare that they use it willingly, the main reasons concern the suitability of part-time work for the production process (20.7%) and the impossibility of employing workers full-time because of budget constraints (4.8%). Only a few firms choose part-time work because they believe that part-timers are more productive than full-timers (2.46%) and to face programmed seasonality (2.05%).

Overall, these preliminary descriptive statistics provide hints that firms might not be particularly keen on offering part-time contracts to their employees. Investigating whether this is related to any detrimental impact of part-time work on a firm's TFP is the objective of the following econometric analysis.

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

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

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

6. Results

6.1. Main Findings

In this section, we explore the impact of part-time work on TFP, focusing on the second-step equation in (4). We refer the reader to Appendix C for details on the TFP estimates obtained in the first step.

Table 4 presents the results from 11 different specifications and/or methods to estimate Equation (4). Recall that, since our preferred estimation method for the first step is ACF-FE, we use the ACF-FE estimates of TFP as the dependent variable in all the following second-step estimations.

The first column shows the OLS estimates of Equation (4) which includes only a basic set of controls: dummies for firm size, year, region, and 3-digit industry, plus year and industry interactions. According to this initial regression, part-time work has a strongly significant negative impact on firm productivity: a 1 standard deviation increase (0.141) in the part-time share reduces the firm productivity by 3.04%.[17]

However, as we pointed out in Section 4, since part-time workers tend to be segregated with respect to gender, jobs, and types of contract (i.e. temporary *versus* permanent), it is safe to control also for these workforce characteristics. This is carried out in Specification (2), which adds the shares of females, non-EU workers, temporary workers, and blue- and white-collar workers to the list of controls already included in Specification (1). According to this model, part-time work still has a negative and significant impact on TFP, though it is smaller: a 1 standard deviation increase in its share brings about a reduction in the firm productivity of about 2.03%. The results suggest that, besides being (in general) positively correlated with the part-time share, these workforce characteristics are negatively related to TFP.[18] Thus, if we fail to control for them, we tend to overestimate the negative impact of part-time work on TFP.

Moreover, the available empirical evidence suggests that part-timers might also be segregated by age and education. Even though we are not able to account for the age and education distribution of the workforce for the whole sample period, we can do so for the year 2010 (Specification (3)). As discussed in Section 3, the characteristics of the management may also influence both the level of part-time work and the TFP. Albeit only for the

[17]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.

[18]In the sample, the shares of females, white-collars, non-EU workers and temporary workers are positively correlated with the share of part-timers, while its correlation with the share of blue-collars is negative but very small (-0.006).

year 2010, we are able to account for several managerial characteristics: the manager's type (i.e. whether he or she is the owner of the firm or an internal/external manager), gender, education, and age (Specification (4)). Comparing Specification (5), which reproduces Specification (2) but only for the year 2010, with Specifications (3) and (4), we can see that these sets of controls do not substantially change the estimate: -0.182 in both (3) and (4) *versus* -0.192 in (5).

Despite our specifications already control for a rich list of potential confounding factors, one may still be concerned that unobservable firm heterogeneity (e.g. managerial ability) might preclude the identification of the causal effect of interest. One way to investigate whether this is the case is to compare our previous findings with those obtained from a FE estimation of Equation (4), thereby removing the omitted variable biases arising from time-invariant unobserved heterogeneity. According to the FE Specification (6), which only includes year and year/industry interaction terms, the effect of part-time work on TFP is still negative and significant at the 10% level. The FE Specification (7) adds the usual workforce controls, specifically, the shares of females, non-EU workers, temporary workers, and blue- and white-collar workers. The estimated coefficient is very similar to the first FE specification (-0.115 *versus* -0.117) and still significant at the 10% level. For comparative purposes, Specification (8) performs an OLS regression as in (2) but on the sample used in the FE estimation. The estimated impact of part-time work is still negative and significant, albeit a little higher in absolute terms than the FE one (-0.169 *versus* -0.117). When assessing these results, it should be noted that FE estimates are known for delivering coefficients biased toward 0, because of the exacerbation of the measurement error induced by the within-firm transformation. Regarding the higher p-value of the part-time coefficient in the FE than in the OLS estimates, it should be noted that the FE method can only be performed on a much smaller sample and with limited within-firm variation due to the short longitudinal dimension of the RIL data.

As discussed in Section 3, an additional concern is that part-time work might be correlated with idiosyncratic productivity shocks to the firm, causing part-time work to be endogenous and hindering the identification of the causal effect of interest. To explore this possibility, we perform a simple IV estimation of Equation (4), in which we instrument part-time work with its 2- or 3-year lag. In practice, in the equation for the year 2010, we instrument the part-time share with its level in 2007, and in the equation for the year 2007, with its level in 2005. Notice that to perform this kind of IV estimation, we lose one year of observations, that is, 2005, and we are forced to consider firms with at least 2 years of consecutive observations. This sharply reduces our sample to only 3,536 observations. The results of this IV estimation are presented in column (9) of Table 4. The estimated impact of part-time work on TFP is still negative, significant at the 1% level and equal to -0.273.[19]

Since this model is exactly identified, we cannot assess the validity (i.e. the exogeneity) of the instrument used. To gain insights into this issue, we perform another IV estimation that, besides instrumenting part-time work 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, to gain overidentification for testing the validity of the orthogonality conditions. 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 (part-time share, in our case) against all the exogenous regressors in the model. Then the 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 work, we use 5 additional instruments constructed on the basis of Equation (5) from the shares of females, non-EU workers, temporary workers, and blue- and white-collar workers. With these 6 instruments for the part-time share, we can then perform the standard IV estimation (Specification (10)). The estimated coefficient is again negative, significant at the 1% level and equal to -0.252. The Hansen-J test for the validity of the overidentifying restrictions indicates that they are valid overall (p-value 0.806). As before, for comparative purposes, we run an OLS regression on the sample used in the IV estimation (Specification (11)), finding similar estimates (-0.195) for the coefficient of part-time work. Comparing the two sets of estimates, we conclude that the potential correlation of part-time work with time-varying productivity shocks is unlikely to represent a major issue for our results in practice.

Before considering a number of robustness checks and extensions, we briefly discuss the association between TFP and the other regressors included in the analysis. Increases in the shares of females, non-EU workers, and blue- and white-collar workers (with respect to managers) are generally associated with a decrease in 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 more beneficial to a firm's TFP than when the owner of the firm also manages it. A negative association is also

[19] Lagged part-time share is a strong predictor of current part-time share, with a first-stage F statistic well above conventional threshold levels.

detected between TFP and female managers, as is the case of young managers (under 40). The results also suggest that TFP increases with the firm size.

Appendix D provides some robustness checks. First, we compare the estimated impact of part-time work on TFP when different TFP estimates are used. Second, we consider the impact of interest only for the period before the crisis (i.e. the years 2005 and 2007). Our main results remain broadly unchanged.

To summarize, we find that part-time work has a negative impact on firm productivity. Our estimates are in line with those reported by Specchia and Vandenberghe (2013) for Belgium. In particular, while they find that a 10 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 the same figure to be slightly higher: 1.45%.[20]

We also find that 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 the correlation of part-time work with productivity shocks, on the other hand, is unlikely to represent a real threat to the identification of the effect of interest. In view of this consideration and given that OLS estimation allows us to exploit the full sample, we take Specification (2) as our reference, both for assessing the effect of part-time work on productivity, as just discussed, and for our extensions, which are discussed below.

6.2. Extensions

Until now, 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 previously been explored.

Table 5 shows the OLS estimates of the separate impacts of horizontal, vertical, and mixed part-time work. Not surprisingly, since it represents most of the part-time work, horizontal part-time work is estimated to have virtually the same impact on TFP as already shown for the general case (-0.148 *versus* -0.146). This result is strongly significant (at the 1% level). Vertical part-time work is also estimated to have a negative impact, though it is very small in magnitude (-0.013) and not significantly different from zero at any conventional level. This result suggests that what really threatens the organizational efficiency of the firm is working shorter hours each day, while working full-time on only some days of the week

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

(or month) does not seem to do so. Mixed part-time work is predicted to have a negative and significant impact on TFP (-0.197): being a mixture of the horizontal and the vertical model, it is presumable that its effect stems from the horizontal component.

In Table 6, we analyze whether the impact of part-time work on TFP is different if the firm passively accepts it as a consequence of workers' requests for shorter hours with respect to the case in which the firm willingly chooses to use it. To answer this question, we divide the sample of firm-year observations using part-time work into two sub-samples: those using part-time work as the result of workers' requests and those that choose to adopt it.[21] The results are consistent with our conjecture: the firms that are 'forced' to use part-time work are the ones that suffer 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 reduction in TFP is only 1.3% for the case in which firms willingly choose to use part-time work. What is surprising is that part-time work is also harmful to those firms that willingly choose to adopt it.[22] One possible reason for this might be that managers fail to anticipate fully the detrimental impact of part-time work on productivity. However, it may also be the result of a consciously weighed trade-off between productivity losses and costs savings if part-timers are discriminated against in terms of hourly pay.

Table 7 investigates whether the impact of part-time work on productivity is different if the firm utilizes elastic and/or flexible clauses. As before, we split the sample of firm-year observations using part-time work into two groups: those that use part-time contracts with clauses and those that do not. We find evidence that using such clauses helps in cushioning the negative effect of part-time work. They contribute to reducing 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 the clauses are used, whereas the same increase causes TFP to decrease by about 1.89% in the case in which they are not used. These results shed light on the role of these clauses as instruments intended to increase the flexibility for the firms in the use of part-time work and, hence, to make them more willing to use it, while allowing individuals to conciliate better their work and private life.

To gain further insights into the potential for clauses to reduce the productivity losses associated with part-time work, the lowest part of Table 7 presents the results of the separate estimation for the 2005 and 2007 waves (i.e. before the part-time reform of 2007[23]) and for

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

[22] Even removing from the sample firms declaring to use part-time work 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.

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

the 2010 wave (i.e. after the reform). Indeed, if the 2003 Biagi's Law was in the direction of 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 shifted in favor of employees. Since then, the *precise* procedure for using elastic and flexible clauses has had to be agreed on the basis of sectoral collective agreements, into which the needs of individual firms cannot be directly incorporated.[24] The results suggest that when Biagi's Law was in force (2005 and 2007), using part-time work with clauses decreased TFP by about 47% less than using it without clauses, whereas using part-time work with clauses in 2010, when the power of firms in relation to the use of clauses was strongly reduced as a result of the 2007 Law, is estimated to have decreased TFP by about 37% less with respect to the case in which clauses were not used. These estimates suggest that the capability of clauses to curtail the productivity inefficiencies caused by part-time work has been substantially reduced as a result of the 2007 Law, by as much as 10 percentage points. This eventually contributes to making firms less willing to grant part-time work to employees who ask for it. An implication of these findings is that introducing more flexibility into the use of part-time work could be a win-win strategy: for firms, which would experience a smaller loss in productivity associated with part-time work, and for workers, since firms would be more willing to offer part-time contracts to those workers who wish to have one.

Finally, Table 8 summarizes the results for the separate impacts of part-time work on TFP by sector of economic activity. We find that part-time work is harmful to 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 the 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 does the impact of part-time work on TFP change its sign, becoming positive, though very small in magnitude (0.006). This result is consistent with the observation that retail shops often have longer opening hours than the typical full-time working time and that they may also experience workload peaks during the day. Under these circumstances, part-time work may have the potential to increase the allocation efficiency, as argued by Künn-Nelen et al. (2013), who report a positive effect for the Dutch pharmacy sector (which belongs to the retail sector). The impact of part-time work also turns positive for the retail sector in the study by Specchia and Vandenberghe (2013). However, notice that this positive effect is never statistically significant at any conventional level in

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

our case.[25]

7. Conclusions

In this paper, we investigate the impact of part-time work on firm TFP through a two-step procedure. In the first step, we use a large panel data set on (almost) all Italian corporations for the period 2000-2010 to obtain 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 unobserved firm heterogeneity into account. 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: a 1 standard deviation increase in the part-time share is estimated to decrease TFP by about 2%. Our emphasis for this result is on the communication and coordination inefficiencies created by part-time work, eventually leading to a decrease in productivity.

We also explore the separate impacts of horizontal, vertical, and mixed part-time work, finding that the negative impact of part-time work is mostly exerted by the horizontal component, while for the vertical model we find no significant impact. This suggests that what really damages a firm's organizational efficiency is the *daily* reduction in the working time. These findings have broad policy implications. For example, more men could be encouraged to take on vertical part-time work (e.g. working four full-time days per week instead of five) with little disruption for firms and for their own careers and to the advantage of their wives/partners' participation in the labor market and the promotion of gender equality.

Moreover, we find that the firms that are 'forced' to use part-time work to accommodate the requests of their workers are the ones that suffer the most from it: the negative impact of part-time work on those firms is almost double with respect to that on firms that adopt it willingly. While this difference is consistent with the expectations, one reason for part-time also being harmful to firms that deliberately choose it may reside in the inability of managers to anticipate correctly the coordination and communication costs related to part-time work. It may also be the result of a consciously weighed trade-off between productivity losses and cost savings in the presence of pay discrimination against part-timers, as suggested by Garnero et al. (2014). More empirical evidence on these issues is needed, offering a potentially fruitful area of exploration for future research.

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

Finally, we find that flexible and elastic clauses are effective in reducing the productivity losses associated with part-time work: the use of such clauses is estimated to decrease the negative impact by about 43%. Considering that a large fraction of firms declare that they use part-time arrangements in response to their employees' requests, these clauses appear to provide an important instrument to increase firms' flexibility in the stodgy usage of part-time work. In this view, flexible and elastic clauses may represent a win-win policy: reducing the negative impact of part-time work on productivity, they render firms more prone to concede part-time arrangements to workers who ask for them. Policy makers should consider encouraging a wider use of such practices in countries and sectors where they are not available, as well as promoting a greater degree of flexibility in the existing schemes.

Table 1: **RIL-AIDA data set: distribution of observations by industry and number of observations**

Industry	**Frequence**	**Percentage**
Manufacturing	6,897	49.76
Construction	2,002	14.44
Trade	1,46	10.58
Transportation and communication	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 data set (years: 2005, 2007 and 2010)

Table 2: **RIL-AIDA data set: sample summary statistics**

Variable	**Mean**	**Std. Dev.**	**1st Q.**	**Median**	**3rd Q.**
Information from AIDA data set					
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 data set					
Employees	103.709	396.895	15	29	69
Female share	0.306	0.245	0.105	0.233	0.462
Non-EU share	0.058	0.110	0	0	0.068
Temporary share	0.105	0.153	0	0.055	0.140
Blue-collars share	0.593	0.299	0.400	0.692	0.822
White-collars 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 data set: 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 data set: 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 data set (years: 2005, 2007 and 2010)
* Computed according to the permanent inventory method. See Appendix B for details.
** Only for the year 2010 (5,912 observations).

Table 3: **RIL-AIDA data set: part-time work; use, types, clauses, and reasons**

	Frequence	**Percentage**
Use of part-time work 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 work		
Horizontal part-time work use	8,710	62.84
Vertical part-time work use	1,407	10.15
Mixed part-time work use	1,061	7.66
Flexible and Elastic Clauses - excluding firms using mixed part-time work		
Horizontal part-time work use	8,041	62.83
of which:		
with flexible clauses	2,721	33.84
without flexible clauses	5,320	66.16
Vertical part-time work 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 work		
Workers' willingness	*6,411*	*67.96*
for accommodating workers' requests for shorter working time	6,411	67.96
Firms' willingness	*2,828*	*29.98*
it is suitable for the production process	1,954	20.71
it is 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 reasons	*195*	*2.07*
Other reasons	195	2.07

Source: RIL-AIDA data set (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)
Non-EU workers 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	3,536	3,536	3,536
Number of firms	9,405	9,405	5,216	5,216	5,216	3,089	3,089	3,089	2,738	2,738	2,738

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

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

Table 5: **Results; extensions: types of part-time work; 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 data set (years: 2005, 2007 and 2010)
All the estimations include the same set of controls as in Specification (2) of Table 4. See the footnote of Table 4.

Table 6: **Results; extensions: reasons for the use of part-time work; estimation method: OLS**

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

	Workers' requests	**Firms' willingness**
Part-time share	-0.254***	-0.134***
	(0.065)	(0.050)
Number of firm-year observations	6,411	2,828

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

Table 7: **Results; extensions: flexible and/or elastic 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 data set (years: 2005, 2007 and 2010)
The estimates are performed on sub-samples of firm-year observations using part-time work (9,434). All the estimations include the same set of controls as in Specification (2) of Table 4. For the rest, see the 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 data set (years: 2005, 2007 and 2010)
All the estimations include the same set of controls used as in Specification (2) of Table 4. For the rest, see the 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:

$$Y_{it} = A_{it} L_{it}^{\beta_l} K_{it}^{\beta_k} \tag{A.1}$$

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

$$A_{it} = exp\{\alpha + \nu_t + \mu_j + \sigma_r + \omega_{it} + \epsilon_{it}\} \tag{A.2}$$

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; and ω_{it} is the time- and firm-specific (i.e. idiosyncratic) deviation from that mean; whereas ϵ_{it} is a measurement error that is by assumption not correlated with the 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 (A.2) and by taking logs in (A.1):

$$y_{it} = \alpha + \beta_l l_{it} + \beta_k k_{it} + \nu_t + \mu_j + \sigma_r + \omega_{it} + \epsilon_{it} \tag{A.3}$$

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 its usage of labor and/or capital.[26] 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 related to ω_{it} which is unobservable to the econometrician and idiosyncratic to the firm. Hence, the rest of the discussion focuses on ω_{it} rather than on the whole expression for (the log of) A_{it} and, for

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

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

$$y_{it} = \alpha + \beta_l l_{it} + \beta_k k_{it} + \omega_{it} + \epsilon_{it} \tag{A.4}$$

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 (A.4) and, consequently, of the TFP[27], inconsistent. According to the assumptions that are made concerning 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 consider to be the most realistic set of assumptions for 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 eliminate the simultaneity problem (i.e. of ω_i) by running an OLS regression on the within-group transformation of (A.4):

$$\widetilde{y}_{it} = \beta_l \widetilde{l}_{it} + \beta_k \widetilde{k}_{it} + \widetilde{\epsilon}_{it} \tag{A.6}$$

where the tilde operator indicates the within-group transformation: $\tilde{x}_{it} = x_{it} - \frac{1}{T}\sum_{t=1}^{T} x_{it}$.[28]

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 our preferred specification is based on an extended version of the method developed by Ackerberg et al. (2006), we concentrate on it here (for a detailed discussion of 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:

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

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

$$lnA_{it} \equiv TFP_{it} = y_{it} - \widehat{\beta}_l l_{it} - \widehat{\beta}_k k_{it} \tag{A.5}$$

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

[28] 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, that is, $E[\xi_{it}|I_{it-1}] = 0$. 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 about ω_{it} using $g(\cdot)$ at $t-1$.

The intermediate inputs, m_{it}, are assumed to be perfectly flexible: the choice of the amount of them to be used at t is made at t (i.e. contemporaneously). Moreover, they are assumed not to have any dynamic implication: m_{it} does not depend on m_{it-1}.[29] 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}:

$$m_{it} = f(l_{it}, k_{it}, \overset{+}{\omega}_{it}) \tag{A.7}$$

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

$$\omega_{it} = f^{-1}(l_{it}, k_{it}, m_{it}) \tag{A.8}$$

This expression for ω_{it} can then be substituted into (A.4) to produce:

$$y_{it} = \alpha + \beta l_{it} + \beta k_{it} + f^{-1}(l_{it}, k_{it}, m_{it}) + \epsilon_{it} \tag{A.9}$$

At this point, ACF propose a two-step strategy to obtain estimates of β_l and β_k. In the first step, y_{it} is non-parametrically regressed against a function in l_{it}, k_{it}, and m_{it}, which we call $\Phi(l_{it}, k_{it}, m_{it})$.[30] 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, that is, β_l^* and β_k^*, it is then possible to obtain the implied ω_{it},

[29] 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).

[30] In our empirical analysis, we approximate $\Phi(\cdot)$ with a second-order polynomial in l_{it}, k_{it} and m_{it}. For robustness, we have also tried with higher orders (third- and forth-order polynomials). However, since this does not substantially alter the results, we have decided to use the second-order approximation.

i.e. $\hat{\omega}_{it}(\beta_l^*, \beta_k^*)$[31], 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, that is, $\omega_{it} = g(\omega_{it-1}) + \xi_{it}$, 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 the residuals from a non-parametric regression of implied $\hat{\omega}_{it}(\beta_l^*, \beta_k^*)$ on implied $\hat{\omega}_{it-1}(\beta_l^*, \beta_k^*)$.[32] In the second step of this procedure, the sample analogues of the moment conditions imposed by our model[33] are evaluated:

$$\begin{aligned} \frac{1}{N}\frac{1}{T}\sum_i \sum_t \hat{\xi}_{it}(\beta_l^*, \beta_k^*) k_{it} = 0 \\ \frac{1}{N}\frac{1}{T}\sum_i \sum_t \hat{\xi}_{it}(\beta_l^*, \beta_k^*) l_{it} = 0 \end{aligned} \tag{A.10}$$

The search over β_l^* and β_k^* continues until $\hat{\beta}_l$ and $\hat{\beta}_k$ are found to satisfy (A.10). These are the ACF estimators of β_l and β_k.

Though the ACF method offers a potential solution to the simultaneity problem, we argue that explicitly accounting for a time-invariant component in the structure of firm productivity, besides the time-varying one, would represent a further enhancement at a relatively low cost. In a nutshell, ACF propose to proxy firm productivity, which is unobservable, through the intermediate inputs' demand. Very powerful though this proxy may be, some of the firm productivity is still likely to be left unexplained. From this perspective, removing the time-invariant part of the productivity would definitely increase the chance of the proxy working well. Following Vandenberghe et al. (2013), we argue that only the first stage of the ACF procedure needs to be modified to account explicitly for firm fixed effects.

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

$$\omega_{it} = \eta_i + \omega_{it}^* \tag{A.11}$$

According to (A.11), the firm productivity is composed of the sum of a time-invariant (η_i) and a time-varying (ω_{it}^*) component. On the one hand, η_i can be thought 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

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

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

[33] 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 $E[\xi_{it} l_{it}] = 0$.

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:

$$m_{it} = f(l_{it}, k_{it}, \omega^*_{it}) \tag{A.12}$$

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 the demand of intermediate inputs depending on η_i; this assumption rules out factors such as management quality, culture, and internationalization of the firm contributing to determining the demand for the intermediate goods to be used in the production process. This does not seem to be an implausible assumption, since it is reasonable to think that the demand for intermediate inputs, which are by assumption perfectly flexible and non-dynamic, depends only on time-varying components. Moreover, we preserve the assumption that f is invertible in ω^*_{it}. This set of assumptions implies that equation (A.9) is modified as follows:

$$y_{it} = \alpha + \beta l_{it} + \beta k_{it} + \eta_i + f^{-1}(l_{it}, k_{it}, m_{it}) + \epsilon_{it} \tag{A.13}$$

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 (A.13) as:

$$y_{it} = \Phi(l_{it}, k_{it}, m_{it}) + \eta_i + \epsilon_{it} \tag{A.14}$$

At this point, we are able to remove η_i from (A.14) by applying (non-parametric) FE estimation.[34] From the FE estimation of (A.14), we are able to obtain a consistent estimate of $\Phi(\cdot)$, that is, $\hat{\Phi}(\cdot)$, so that it is possible to proceed to the (unchanged with respect to the ACF method) second stage of the estimation from: $\widehat{\Phi}_{it} = \widehat{\alpha + \beta_l l_{it} + \beta_k k_{it} + \omega^*_{it}}$.

[34] 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 non-parametric FE estimation, since they are time invariant.

B. The AIDA data set

The data set used in our analysis is the result of some cleaning with respect to the original version. We remove firms belonging to the mining industry (there are a few) and to sectors in which the level of public intervention is substantial, such as the 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. 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, to perform LP, ACF, and ACF-FE estimations, we have to restrict our attention to firms for which we have at least 2 *consecutive* years of observations.

The final data set is made up of 2,406,612 firm-year observations for 440,953 firms. While for 8.08% of the firms we have the complete observation window (11 years), for half of them we have more than 5 years of observations. Table B.1 shows the distribution of the AIDA data set across the 40 sectors (2-digit Ateco 2002 classification) for which we estimate a separate production function. As shown in Table B.1, about one-third of the observations belong to the manufacturing industry. The trade and services sectors cover respectively about 29% and 21% of the observations, while the remaining observations are split between the construction industry (14.1%) and the transportation and communication industry (4.18%).

Table B.1: **AIDA data set: 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

Table B.1: **AIDA data set: distribution of observations by sector of economic activity (2-digit Ateco 2002) - continued**

Sector of economic activity	**Frequence**	**Percentage**
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 motor vehicles)	373,492	15.52
Retail (excluding motor vehicles)	219,955	9.14
Transportation and communication	*100,544*	*4.18*
Land transportation/transportation by pipeline	53,030	2.20
Maritime transportation	1,973	0.08
Air transport	578	0.02
Auxiliary transportation activities	40,775	1.69
Post and telecommunication	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 data set (period: 2000-2010)

C. The TFP estimates

Table C.1 shows the correlation matrix of the different TFP estimates, while Table C.2 shows their summary statistics. The different TFP estimates are positively and highly correlated: the correlation coefficients range between 0.826 and 0.968 (for a similar finding, see Van Beveren, 2012). The ACF and ACF-FE estimates are very similar with respect to the OLS estimates (the 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 (natural logarithm of the) TFP estimates ranges between 3.061 for the OLS estimates and 5.506 for the FE estimates. This suggests that the simultaneity issue, though conceptually relevant, loses 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 D.1).

Table C.1: **AIDA data set: correlation matrix of different estimates of 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 data set (period: 2000-2010)

Table C.2: **AIDA data set: summary statistics of different estimates of 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 data set (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). The results confirm that the part-time effect on TFP is also significantly negative (at the 5% level) for the pre-crisis period and not substantially different from the general effect (-0.099 *versus* -0.146).

Table D.1 shows the results for the impact of part-time work 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 work on TFP is negative, regardless of which first-step estimation method is used. However, the magnitude of the impact differs somewhat across the methods, ranging between -0.233, when the LP estimates of 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 to those stemming from the simple OLS estimation of TFP. On the contrary, the FE and LP estimations, which are most likely to suffer from the well-known 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 D.1: **Results; robustness checks: OLS, FE, LP, and ACF estimates of 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 data set (years: 2005, 2007 and 2010)
The estimation includes the same set of controls as in Specification (2) of Table 4. For the rest, see the footnote of Table 4.

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