The Impact of Sickness Absenteeism on Firm Productivity: New Evidence from Belgian Matched Employer-Employee Panel Data

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Abstract

Using rich longitudinal matched employer-employee data for Belgium, we provide a first investigation of the impact of sickness absenteeism on firms' productivity. To do so, we estimate a production function augmented with a firm-level measure of sickness absenteeism that we constructed from worker-level information on non-worked hours due to illness or injury. We deal with the endogeneity of inputs and sickness absenteeism by applying a modified version of the semiparametric control function method developed by Ackerberg et al. (2015), which explicitly takes firm fixed unobserved heterogeneity into account. Our main finding is that, in general, sickness absenteeism substantially dampens firms' productivity. However, further analyses show that the impact varies according to several workforce and firm characteristics. Sickness absenteeism is more detrimental to firm productivity when absent workers are high-tenure or blue-collar. Moreover, it is especially harmful to industrial, capital-intensive, and small enterprises. These findings are consistent with the idea that sickness absenteeism is more problematic when absent workers have in-depth firm/task-specific knowledge, when the employees' work is highly interconnected (e.g., along the assembly line), and when firms face more organizational limitations in substituting absent workers.

Keywords: Sickness absenteeism, firm productivity, workplace well-being programs, semiparametric control function methods for the estimation of firm-level production functions, longitudinal matched employer-employee data.
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1. Introduction

Sickness absenteeism is a phenomenon that consists in workers' absence from work due to illness or injury (Niedhammer et al., 1998). According to the World Health Organization (WHO), an average of 11.9 days of work per employee were lost in the EU in 2014 due to illness or injury. The Bureau of Labor Statistics reports that 2% of working time was lost due to sickness in the US in 2018.

It has long been acknowledged that sickness absenteeism imposes a considerable cost on advanced industrialized societies (Eurofound, 2010, 1997). This cost is borne by different actors, notably workers, firms, and insurance providers. Concerning the individual worker, in addition to the pain and suffering caused by sickness and to the potential extra expenditure on the necessary care, sickness absenteeism often causes a loss in labor income, especially in case of long absence periods.[1] Firms are also affected by sickness absenteeism. They often bear part of the costs of sickness benefits. Depending on the institutional regime, the sickness benefits paid by the employers can represent the totality of the worker's income, at least for short-term sickness absence. Firms typically need to resort to (costly) overtime work or substitute workers to temporarily replace absent workers, thus incurring additional expenses. Apart from these direct costs, it is widely acknowledged that there is a significant indirect cost that firms likely bear due to sickness absence: diminished productivity (Eurofound, 2010, 1997; OECD, 2009b, 2005; Gimeno et al., 2004; Whitaker, 2001). Overtime work and substitute workers might be less productive than the absent workers and might not be easy to find on short notice, especially under specific circumstances, such as when the firm faces organizational limitations preventing it to optimally staff its workforce or when absent workers are those more experienced. Finally, insurance companies, which are typically the governments in EU countries, also incur a considerable cost due to sickness absence. Usually, they are required to pay (a share of) the income of employees that are absent due to sickness. If the workers' health problems go on for a long time, the workers are more likely to enter disability (OECD, 2009b), whereby they typically receive (permanent) disability benefits. In summary, the costs associated with ill health and injuries may potentially have a substantial effect on a country's economy.

National and supranational authorities have long tried to estimate the costs associated with sickness absenteeism. As expected, these costs indeed appear to be considerable. For instance, back in the 1990s, it was estimated that sickness absenteeism represented a cost of

[1] Sickness benefits usually decrease with the duration of sickness absenteeism. Moreover, the first day(s) of sickness absence is/are often not paid, either by the national insurance system or by the employer, so that the worker loses the totality of the income for that initial period.

more than 11 billion Pounds (16.3 billion US Dollars) per year in lost production in the UK and over 60 billion German Marks (34.6 billion US Dollars) in social security insurance paid by employers in Germany. In 1995, Belgium was estimated to spend 93 billion Belgian Francs (2.6 billion US Dollars) for sickness benefits and 21 billion Belgian Francs (0.6 billion US Dollars) for benefits on work accidents and occupational diseases (Eurofound, 1997). In more recent years, Eurofound estimated that the costs of sickness absenteeism for governments range between 1% and 2% of EU countries' gross domestic products (Eurofound, 2010). In the US, the costs of sickness absenteeism for firms are similarly high. Losses in production related to health problems were estimated to cost US employers a total of 225.8 billion US Dollars annually (Stewart et al., 2003).

National governments have thus made it a top policy priority to address sickness absenteeism. In some countries, such as Sweden, sickness absenteeism is even considered an alarming problem: in Sweden, the absenteeism rate due to sickness is uncommonly high, and the government is urgently taking active steps to try to enhance people's health and reduce sickness-related absences from work (OECD, 2005).

However, estimating the actual costs of sickness absenteeism is not an easy task. The direct costs of sickness absenteeism, which include sickness benefits paid by firms and insurance systems, are difficult to estimate, especially when it comes to cross-country comparisons, and estimating the indirect effects from official statistics, such as productivity losses suffered by firms, proves to be even more complicated, if not impossible (Eurofound, 2010).

In this paper, we contribute to the measurement of the costs that sickness absenteeism imposes on society by concentrating on one fundamental aspect: firm productivity. We focus on firm productivity because productivity growth is well-known to be a crucial determinant of sustained and sustainable economic growth (Jorgenson, 1988), and the potential for sickness absenteeism to have a substantial impact on productivity is high. It is essential for researchers in economic disciplines to understand which factors influence productivity and in what way. Although a small but compelling line of literature has deepened our knowledge of how several labor-related issues impact productivity in recent years (e.g., Devicienti et al., 2018; Giuliano et al., 2017; Vandenberghe, 2012), there has not been, to our knowledge, any empirical study analyzing the impact of sickness absenteeism on productivity.

This lack of studies on sickness absenteeism is attributable to data limitations. On the one hand, matched employer-employee data, which allow constructing detailed workforce characteristics, including absences, have been available for a relatively short time (Card et al., 2014). On the other hand, sickness absenteeism has not yet been explicitly analyzed due to the impossibility of distinguishing between the various types of absenteeism (Zhang et al., 2017). Instead, a vast literature assessing the determinants and dynamics of sickness absenteeism - which resorts to individual-level data - testifies the attention that the academic community has placed on this theme (e.g., Arnold et al., 2018; Battisti and Vallanti, 2013; Dionne and Dostie, 2007).

Examining the specific impact of sickness absenteeism in the firm, as opposed to total absenteeism, is crucial for several reasons. First, excluding maternity leaves, health-related problems are the most common cause of absenteeism (Eurofound, 2010). Therefore, sickness absenteeism constitutes a predominant portion of total absenteeism.

Second, it is crucial from a policy perspective. Sickness involves considerations on people's health, which are fundamental not only for ethical reasons, but also for economic reasons. Costs due to ill health are enormous, and understanding the dynamics and causes of such costs, especially of indirect ones, is fundamental to give policy-makers the appropriate instruments to reduce them. Assessing the impact of sickness absenteeism on firms' productivity is also critical to evaluate the potential for incentivizing firms to keep sickness absenteeism levels low. Employers can do much on this front. Working conditions and security at work are crucial determinants of illness (e.g., mental problems caused by poor working conditions, see Bubonya et al., 2017) and injuries. One of the steps already taken by several governments (including Belgium) to reduce sickness absenteeism was to introduce the employer's responsibility to pay sickness benefits at the beginning of sickness absence. Understanding the indirect costs that firms incur due to sickness absenteeism is thus crucial to stimulate their active involvement in sickness prevention and worker reintegration.

Third, sickness absenteeism is fundamentally different from other types of absences, such as holidays, educational leaves, maternity leaves, or sabbatical leaves: it follows different dynamics and has different implications in terms of margins of interventions. On the one hand, sickness is highly unpredictable: firms can hardly predict when a worker will fall ill or be injured. In comparison, it is much easier to predict when a worker will start her maternity leave - this is usually known several months in advance, or his/her holidays - this is usually planned and agreed with the employer months before. These different degrees of predictability might result in the various types of absenteeism causing differentiated effects on productivity. Estimating the impact of the overall level of absenteeism and extending it to sickness absenteeism might thus be misleading. On the other hand, employers have margins of intervention concerning sickness absence, especially as regards to work-related injuries and health problems, whereas they have no (or very small) margins of intervention for events such as the health problems or death of a worker's close family member, or other family-related commitments.

Our aims and main contributions to the literature are twofold. First, we seek to obtain a consistent estimate of the impact of sickness absenteeism on productivity and, hence, to reliably assess the magnitude of this impact. Second, we aim to understand whether and how the impact of sickness absenteeism on productivity depends on several workforce and firm characteristics that may be relevant, such as the categories of absent workers and the firm's industry, type of technology, and size.

We perform our empirical analysis by using uniquely rich matched employer-employee data on Belgian private firms over the period 1999-2007. Thanks to detailed information on each employee's worked and non-worked hours, we can construct a measure of the firm's rate of sickness absenteeism. The unique feature of our data is that it allows us to distinguish between absenteeism certainly due to sickness from other types of absenteeism (e.g., educational leave and other personal leaves). However, due to data limitations, we are forced to concentrate on short-term sickness absenteeism, which nonetheless constitutes a substantial fraction of total sickness absenteeism (Chimed-Ochir et al., 2019). Moreover, the matched employer-employee nature of our data allows us to compute rates of sickness absenteeism that are specific to several categories of workers (e.g., blue-collar *versus* white-collar workers, or workers with high *versus* low tenure). We estimate a production function augmented with this firm-level rate of (short-term) sickness absenteeism. We address the endogeneity problems due to unobserved firm heterogeneity and simultaneity by adopting a modified version of the semiparametric control function approach designed by Ackerberg et al. (2015) and recently developed by Lee et al. (2019), which explicitly removes firm fixed effects.

As expected, our main finding is that sickness absenteeism is, in general, significantly detrimental to firm productivity. The magnitude of the impact is considerable. According to our estimates, an increase of 1 percentage point in the rate of sickness absenteeism results in a productivity loss of 0.66%.

Moreover, we find that the effect of sickness absenteeism is substantially diversified across categories of workers. The impact is large and significant when high-tenure workers are those absent, whereas it is not significant for low-tenure workers. When we look at occupations, the impact of blue-collar workers' sickness absenteeism is substantially higher than that of white-collar workers, even if it remains rather large and significant for the latter too. We also find that the impact differs across firms. The negative impact is significantly higher for industrial firms compared to non-industrial businesses, which nonetheless experiment a negative and significant impact. A similar picture emerges when we analyze the firm's type of technology: productivity losses due to sickness absenteeism are significantly higher in capital-intensive companies, even if they remain negative and significant in low capital-intensive firms. Finally, we find that small firms, which represent a large fraction of firms in Belgium, are substantially impacted by sickness absenteeism. Conversely, medium-sized and large firms seem not to bear significant productivity losses due to sickness absence.

Our results have broad policy implications. In short, they urge both policy-makers and managers to invest more in employees' health, particularly for those workers and in those firms for which sickness absenteeism is substantially disruptive. More investment in employees' health by firms can represent a win-win strategy: employees could benefit from improved health, and firms could benefit from productivity gains due to reduced sickness absence.

The rest of the paper is structured as follows. Section 2 discusses the theoretical mechanisms, develops a set of testable hypotheses, and presents a literature review of previous empirical works. Section 3 presents our empirical model and identification strategy. Section 4 presents institutional details for Belgium, and sets it in an international perspective. Section 5 describes the data and shows relevant sample descriptive statistics. Section 6 presents and discusses results. Section 7 concludes and draws policy implications.

2. Theoretical framework, hypotheses development, and previous empirical literature

Many scholars and institutions have highlighted that sickness absenteeism is costly for firms (Eurofound, 2010, 1997; OECD, 2009b, 2005; Gimeno et al., 2004; Whitaker, 2001). The seminal paper by Allen (1983) synthesizes the main costs an absent worker imposes on companies, and this review of the theoretical channels behind the impact of sickness absenteeism on productivity significantly builds on his work.

Sickness absenteeism directly affects the firm's labor costs. In most countries, including Belgium, firms have to pay their workers while they are absent due to illness or injury, at least for short-term sickness absence. If firms want to get the work of the absent workers done, they need to either pay overtime hours to other workers or hire temporary substitute workers. When choosing the latter option, they likely bear other costs, such as those related to recruitment and training. Sickness absenteeism may also have indirect effects that increase a firm's labor costs: higher wages may be the price to pay in order to gain workers' adhesion to stricter sickness absenteeism provisions.

Apart from these adverse effects on the firm's total wage bill, sickness absenteeism also imposes losses on productivity. If firms choose not to use overtime or temporary substitute workers, they experience a loss of output at least equal to the output produced by the absent workers. This output loss becomes heavier if the absent workers perform a work that is highly interconnected with the work of other employees (see also Pauly et al., 2002). In this case, workers' absence not only causes the loss of output produced by the absent workers, but also results in productivity losses for the other workers, which may take place in the form of organizational problems, information inefficiencies, and transaction costs. A case in point is assembly-line production, in which the tasks of the different employees are deeply interconnected (Coles et al., 2007). Other examples include teamwork in teams with expanded decision-making and responsibility, such as project management teams (Heywood et al., 2008).

Even when resorting to overtime or temporary substitute workers, productivity losses are likely to occur. These solutions may result in lower productivity than that of the absent workers. This is especially critical if the absent workers have in-depth firm/task-specific knowledge, which makes it difficult to find temporary replacements (see also Pauly et al., 2002). If the tacit knowledge of the absent workers about the firm and tasks' processes and routines is in-depth, productivity losses likely increase, as that knowledge resides in the mind of the absent workers and cannot be formalized or transferred to others (Grant, 1996; Nonaka, 1994). Moreover, if the work of the absent employees is highly interconnected with the work of the other employees, the reduced productivity of overtime or temporary substitute workers slows down the work of the other employees.

Furthermore, staffing employees to perform the work of the absent employees may not be straightforward. At the same time, temporary substitute workers may be difficult to find on short notice, thus causing organizational problems that dampen productivity. This may be particularly relevant for small firms, where organizational difficulties in optimally staffing the workforce may make it difficult for the other employees to perform the work of the absent workers, and where recruitment processes may not be as efficient and as fast as in larger firms (OECD, 1997; Pauly et al., 2002).

While these channels are compatible with any type of absenteeism, it is crucial to stress that isolating the impact of sickness absenteeism from absenteeism due to other reasons, such as maternity leaves or personal leaves, is fundamental. The latter types of absences are radically different from sickness absence, which might materialize in differentiated productivity impacts. As highlighted in the introductory section, the degree of predictability of sickness absences is arguably much different from that of other types of absences, such as maternity leaves, holidays, sabbatical leaves, educational leaves, or wedding leaves, which are usually known by firms (and possibly planned together with employers) well in advance. Holidays, for instance, are typically agreed with the employer months in advance. The starting date of the maternity leave is also usually known a few months ahead by firms, and so it is for sabbatical leaves or educational leaves. Therefore, the scope for the disruptive effects on productivity highlighted earlier might be substantially reduced in those cases because firms would typically have the time to find suitable substitute workers and staff the employees to perform the work of those absent.

Furthermore, these other types of absences are likely to have additional theoretical implications that sickness absences do not have, which might further differentiate their effects on productivity from that of sickness absenteeism. It is well known that work-life balance programs are beneficial to firms' productivity (Bloom et al., 2009). Firms with more liberal policies on personal leaves (e.g., holidays or leaves for family-related commitments) - and thus higher levels of absenteeism due to personal reasons - may thus experience productivity improvements, *via* increased commitment, loyalty, and morale of employees. In summary, extending the productivity impact of total absenteeism to sickness absenteeism can be misleading. This is crucial when the objective is to estimate the actual costs of sickness absenteeism, as in our case.[2]

From the discussion so far, it has emerged that sickness absenteeism likely imposes significant productivity losses on firms. However, a zero rate of sickness absenteeism may not be an optimal (and realistic) goal for firms (d'Errico et al., 2016; Pauly et al., 2008). A zero level of sickness absence comes with a downside: presenteeism, that is, going to work while sick (Dew et al., 2005; Johns, 2010). Presenteeism might have adverse effects too. Sick workers might not be as productive as usual and cause other harmful effects. For instance, employees with influenza or flu symptoms are contagious: in such cases, it may be more efficient for sick workers to stay home and heal completely before going back to work (OECD, 2011). In summary, reducing sickness absenteeism appears to be an essential goal for firms (and societies), and this goal should not be achieved by increasing presenteeism, but by effectively improving employees' health.

Given these considerations, we can draw a set of four hypotheses, which we will test in our empirical analysis. These hypotheses can be written as follows:

Hypothesis 1: The impact of sickness absenteeism on productivity is negative.

Hypothesis 2: The impact of sickness absenteeism on productivity is stronger when absent workers have high levels of firm/task-specific (tacit) knowledge.

Hypothesis 3: The impact of sickness absenteeism on productivity is stronger when the work of absent employees is highly interconnected with the work of other employees (e.g., along the assembly line).

Hypothesis 4: The impact of sickness absenteeism on productivity is stronger in small enterprises.

[2]In our empirical analysis, we carried out robustness checks to assess the differentiated impact of sickness absenteeism *versus* total absenteeism and, hence, to assess the magnitude of the bias one would get by not distinguishing the different reasons for absenteeism (see Appendix D and discussion in Subsection 6.1). We anticipate that the bias one would get in this case leads to dramatically distorted conclusions. We thank two anonymous referees for having raised this comment.

To our knowledge, no study explores the impact of sickness absenteeism on firm productivity, but a few empirical studies explore the impact of total absenteeism on productivity.[3] Allen (1983) uses US plant-level data matched with information on absenteeism rates at the industry level and ordinary least squares (OLS) estimations, and finds a negative and significant, yet small, relation with productivity. According to his estimations, an increase by 1 percentage point in the absenteeism rate is associated with a decrease in productivity by 0.16%. More recently, Zhang et al. (2017) focus on Canadian panel data and find that absenteeism (excluding that derived from maternity leaves) is significantly associated with decreased productivity. According to their estimates, an increase of 1 percentage point in the total absenteeism rate is associated with a 0.44% decrease in productivity.[4] Given that these studies do not isolate the impact of sickness absenteeism from that of other types of absenteeism, their results are hardly comparable with ours.

This lack of studies on the impact of sickness absenteeism on productivity is not attributable to a scarce interest in this theme by the academic community and policy-makers. On the contrary, understanding the dynamics and impacts of sickness absenteeism on firms is a priority for many governments, as they bear huge costs due to sickness absences and try to individuate the right incentives for firms to get involved in actively enhancing workers' health and safety at work (Eurofound, 2010; OECD, 2009b). The attention that the academic literature placed on these themes is testified by the vast number of studies assessing the determinants and consequences of sickness absences at the individual level (among the others, see Arnold et al., 2018; Battisti and Vallanti, 2013; Dionne and Dostie, 2007; Frick and Malo, 2008; Ichino and Riphahn, 2005; Markussen et al., 2011). The absence of studies assessing the productivity losses imposed on firms by sickness absenteeism is instead attributable to data limitations. First, matched employer-employee data, which are needed to construct firm-level measures of workers' absences, have only started to be available to researchers in recent years (Abowd and Kramarz, 1999; Card et al., 2014). Second, in the few cases in which absences are reported, they typically do not provide separate information for the different categories of absenteeism, thus not allowing to focus on particular types of absenteeism, such as sickness absenteeism (Zhang et al., 2017). On the other hand, Zhang

[3]Instead, a relatively well-developed line of research assesses the impact of total absenteeism on such variables as the firm's total wage bill, its financial performance, and its monitoring costs (e.g., Allen, 1983; Coles et al., 2007; Godøy, 2017; Heywood et al., 2008; Nicholson et al., 2006; Zhang et al., 2017). As one might expect, these studies point to increased costs (mainly, labor costs) associated with total absenteeism.

[4]Herrmann and Rockoff (2012) and Miller et al. (2008) also recently explored the impact of absenteeism on productivity. However, their studies focused on teachers and their students' scores, which makes their results not directly transferable to the whole private sector. Both studies found negative and significant relations between teachers' absenteeism levels and students' performance.

et al. (2017) clearly state in their paper that they are interested in the effect of sickness absenteeism on productivity, rather than on total absenteeism. However, they are only able to isolate that part of absenteeism certainly not related to maternity leaves. While this measure of absenteeism allows a nearer estimation of the level of sickness absenteeism, it still comprises other components of absenteeism such as personal leaves and holidays, which can result in a substantially biased (i.e., likely underestimated) effect of sickness absences.

3. Empirical model and identification

To explore the effect of sickness absenteeism on productivity, we use the following augmented value-added log-linear Cobb-Douglas production function:

$$y_{it} = \alpha + \beta_l l_{it} + \beta_k k_{it} + \theta SABS_{it} + \gamma X_{it} + \delta C_{it} + u_{it}. \tag{1}$$

The terms y_{it}, l_{it}, and k_{it} stand for (natural logarithms of) value added and labor and capital usage of firm i at time t, respectively. The variable $SABS_{it}$ measures the level of sickness absenteeism in firm i and time t and is our regressor of interest. The term X_{it} is a vector of additional inputs to the production process related to the composition of the workforce. It includes the shares of females, migrants, temporary workers, part-timers, and low-tenure workers, as well as the distributions of the workforce by age, education, and occupation. We also include a number of control variables C_{it}, which are dummies for whether the firm has an "in-house" collective agreement (in addition to an industry agreement) and whether it is an old firm, and dummies for year, size, region, and industry.[5] Finally, u_{it} is the error term, that is, the production level of firm i at time t that remains unexplained. We decompose it into two parts, $u_{it} = \omega_{it} + \epsilon_{it}$ The first, ω_{it}, is the firm's productivity level at t that is not observed by the econometrician but is partly anticipated at $t-1$ and observed at t by the firm. The second, ϵ_{it}, is an idiosyncratic error term assumed to be uncorrelated with regressors.

This empirical setting is commonly called "augmented production function". It hinges on the idea that the firm's production output is influenced not only by standard inputs such as the amounts of labor and capital but also by other production factors, which include the most diverse variables (e.g., workforce composition). It is commonly used in the literature investigating how firm productivity responds to different variables (see, for instance, Parrotta and Pozzoli, 2012, who concentrate on worker mobility, or Konings and Vanormelingen,

[5] Region and industry dummies are excluded in specifications that account for firm fixed effects, since they are time-invariant.

2015, who focus on training). The coefficient of interest, θ, captures the impact of sickness absenteeism on the firms' overall productive performance (i.e., actually, its marginal contribution to production output). The discussion in Section 2 presented various mechanisms through which sickness absenteeism can affect firm productivity (output loss due to absent workers, lower productivity of substitute workers, etc.), and θ gives a measure of the impact of these mechanisms on productivity.[6]

As our first aim is to assess whether and to what extent sickness absenteeism dampens firm productivity, it is essential to estimate θ consistently. For this purpose, the empirical analysis needs to address several endogeneity problems originating from the possibility that inputs and sickness absenteeism might respond to the firm's productivity level ω_{it}, which the firm observes and partly predicts, whereas the econometrician does not.

The first problem has been well documented since the seminal work of Marschak and Andrews Jr. (1944) and is commonly known as "simultaneity of inputs". It relates to the fact that inputs are endogenous since they respond to the firm's productivity level. For instance, highly productive firms will be willing to produce more, thus using more inputs. Likewise, productivity enhancements (e.g., thanks to the introduction of new process technologies) will raise the usage of inputs. This makes inputs correlated with ω_{it}.

The second issue, specific to our study, is that sickness absenteeism is also endogenous.

First, there is an omitted variable bias: some firm characteristics, unobserved by the econometrician, influence both productivity and sickness absenteeism. The firm's management quality is an example. Good managers may take greater care of their employees' health and invest more in employee-friendly work environments (e.g., aiming to limit workers' stress during work), thus achieving lower levels of sickness absenteeism. At the same time, good managers likely reach higher productivity levels, also thanks to measures unrelated to enhancing workers' health. A similar bias may also emerge due to other unobserved firm characteristics that can impact both productivity and sickness absenteeism, such as the degree of competition that the firm faces or its involvement in foreign markets. This results

[6]Note that Equation (1) is coherent with modeling the production function of the firm as the union between a set of "standard inputs" (e.g., labor and capital) and a total factor productivity (TFP) term, typically intended as a firm-wide productivity measure, which basically captures the level of production not explained by the standard inputs and which one can model with relevant variables. In practice, one could start modeling the firm's production function as $Y_{it} = A_{it}L_{it}^{\beta_l}K_{it}^{\beta_k}$, where Y_{it} is value added, L_{it} and K_{it} are labor and capital, and A_{it} is the total factor productivity term. One can then model A_{it} as $A_{it} = exp\{\alpha + \theta SABS_{it} + \gamma X_{it} + \delta C_{it} + u_{it}\}$. By using these two equations and taking natural logarithms, one gets the augmented production function in Equation (1), which is the equation to be estimated in practice. Alternatively, and with no changes in the resulting estimating equation, one could enter the regressor of interest $SABS_{it}$ in a "quality-adjusted" labor input, rather than among the determinants of the firm's TFP (e.g., as in Konings and Vanormelingen, 2015).

in a correlation between sickness absenteeism and ω_{it}.

Second, there is a problem of reverse causality if sickness absenteeism affects productivity and is, at the same time, influenced by it. This may happen when productivity/demand booms require employees to work more intensely, which may negatively affect their health and increase sickness absenteeism (e.g., workers may be subject to increased stress from work). It may also happen that periods of economic downturns or productivity troubles negatively impact workers' health and, therefore, increase sickness absenteeism (e.g., workers may be more exposed to psychological sufferings such as anxiety and depression). Again, this creates a correlation between sickness absenteeism and ω_{it}.

Due to these endogeneity problems, the OLS estimation cannot consistently estimate θ (and the other production function parameters, β_l, β_k, and γ). The fixed effects (FE) estimation (Mundlak, 1961) cannot do so either, even though it removes the time-invariant firm-specific productivity level. It would deliver consistent estimates only under two rather unlikely circumstances: i) if the omitted variable bias derives exclusively from unobserved time-invariant variables, and ii) if inputs and sickness absenteeism do not respond to time-varying unobserved (by the econometrician) productivity levels. Hence, an estimation strategy is needed that can account for a more realistic picture, whereby the unobserved productivity level can fluctuate over time, and production inputs are allowed to respond to these fluctuations.

Over the past few decades, several methods have been proposed for consistently estimating firm-level production functions. Among these, the control function estimators (CFEs), introduced by the seminal work of Olley and Pakes (1996), are now widely used in applied studies and represent the standard way of estimating firm-level production functions (Ackerberg et al., 2015). Within these models, the researcher can adapt production functions augmented with any variable of interest, such as sickness absenteeism, as in our case. These methods have thus been used in many studies assessing the impact of different factors on productivity. Among the most influential, we may cite Konings and Vanormelingen (2015), who concentrated on training, Parrotta and Pozzoli (2012), who focused on learning-by-hiring effects, Serafinelli (2019), who explored spillover effects due to worker mobility, and Vandenberghe (2012), who explored the impact of workforce diversity in terms of age and gender. These estimators rest on complex structural econometric models, but they are based on a simple idea: endogeneity problems due to the unobserved productivity level ω_{it} can be solved by proxying it through a function of observables, called "control function". In practice, CFEs hinge on two main points: i) the identification of a proxy variable, which is assumed to be a function of the unobserved productivity level ω_{it}, and ii) the definition of the conditions under which this function is invertible in ω_{it}.

As mentioned, a first CFE was proposed by Olley and Pakes (1996) (OP), where investments were used as a proxy variable to set up the control function. In practice, the OP method is based on two steps. The first step uses semiparametric methods to estimate the parameters associated with perfectly variable inputs and a nonparametric function which links the unobserved productivity level to capital and investments. In the second stage, the coefficient of the capital input is estimated thanks to assumptions made on the dynamics regulating the stochastic process of the unobserved productivity level and the timing of the choice of the capital input.

Since the work of Levinsohn and Petrin (2003) (LP), the use of investments as a proxy variable has been questioned, due to two main issues. First, investments are typically characterized by high lumpiness, which creates problems in the invertibility of the control function. Second, the OP approach excludes observations with zero investments, which usually induces a significant truncation bias. LP then proposed to use intermediate inputs instead of investments as a proxy variable to set up the control function for the unobserved productivity level. Using intermediate inputs instead of investments represents a substantial improvement. First, intermediate inputs are typically free from adjustment costs, which makes them more reactive to unobserved productivity shocks and hence more able to capture (and thus control for) them. Second, firms typically have positive levels of intermediate inputs, which prevents the truncation problem mentioned earlier.[7]

However, since the work by Bond and Söderbom (2005) (BS) and Ackerberg et al. (2015) (ACF), the OP and LP approaches have been criticized due to collinearity and identification problems. In particular, BS have shown that the parameters of the Cobb-Douglas production function are not identified from cross-section variation if all inputs are perfectly flexible and input prices are common to all firms. Similarly, ACF have demonstrated that there is a problem in the first stage of the OP and LP approaches, because collinearity between labor and the nonparametric terms (i.e., those incorporating capital and the proxy variable) hinder the identification of the labor coefficient. ACF have thus introduced a new CFE which uses intermediate inputs to build the control function and solves the collinearity and identification issues of the OP and LP approaches. The main novelty in the ACF framework is that the intermediate input demand function to invert out to control for the unobserved productivity level is a "conditional" rather than an "unconditional" demand function, whereby labor

[7]In our empirical analysis, intermediate inputs encompass a large number of elements, ranging from the expenditure in raw materials (including energy), to semi-finished goods and external services. This broad definition of intermediate goods ensures positive levels of the proxy variable also for sectors that typically do not produce goods, such as services and trade industries. For robustness, we nonetheless run separate analyses in industrial and non-industrial sectors (see Subsection 6.2).

enters the function together with capital and the unobserved productivity level. This results in a first stage that, unlike in the OP and LP approaches, does not identify the coefficients on variable inputs (e.g., labor). Instead, all coefficients are estimated in the second stage of the procedure. However, the first stage is still crucial to net out the untransmitted error component ϵ_{it} from the production function (Ackerberg et al., 2015).

Like the OP and LP methods, the ACF procedure assumes that unobserved productivity follows a first-order Markov process that is homogeneous for all firms. However, substantial and persistent differences in productivity levels, which are consistent with firm-specific fixed components in productivity levels, have been found ubiquitously in the data (Syverson, 2011). Not explicitly accounting for them could significantly hinder the ability of CFEs to solve the simultaneity bias (Lee et al., 2019). Lee et al. (2019) have thus recently proposed a way to extend CFEs, including ACF, to explicitly account for firm fixed effects, whereby it is allowed for firm-specific persistence in productivity levels. On the one hand, this ensures that unobserved fixed firm heterogeneity is eliminated. On the other hand, it also improves the ability of the proxy variable to capture and control for the (fluctuations in the) unobserved productivity level. As outlined in Lee et al. (2019), the CFEs augmented with fixed effects (CFE-FE) involve only minimal modification to the standard methods, which can be easily implemented in practice.

In this empirical analysis, we present several estimations of Equation (1), including OLS, FE, ACF, and ACF-FE[8]. Given the above discussion, we select the ACF-FE as our preferred method. Appendix A provides a detailed description of our empirical framework and illustrates in detail the ACF and ACF-FE estimation methods.

4. The Belgian case in an international perspective

Sick pay and sickness benefit schemes vary widely among advanced economies (OECD, 2010; Chaupain-Guillot and Guillot, 2017; Rho et al., 2009). Three important notions should be distinguished to qualify this heterogeneity: sick leave, sick pay, and sickness benefits (EC, 2016). Sick leave concerns workers' right to be absent from work due to sickness (i.e., illness or injury) and to return to work after recovering. Sick pay refers to the payment, for a limited period, of (at least part of) workers' wages by their employers during their sick leave. Sickness benefits are the allowances granted to workers by the social protection system in case of sickness absence. They generally correspond to a lump sum or a fraction of workers' previous capped earnings.

[8] "ACF-FE" is the way we refer to the ACF method with the extension proposed by Lee et al. (2019) to explicitly account for firm fixed effects.

Sick leave and sickness benefits are provided in all EU countries. In most of these, employees are also entitled to sick pay, either by law, through collective agreements, or at their employers' discretion. "A double payment arrangement" is thus prevailing in almost all EU countries, whereby after an initial period of income compensation by the employer, benefits are provided by the social protection system (EC, 2016). However, the eligibility conditions, duration, and replacement rates of sick pay and sickness benefits vary substantially from one EU country to the other. Eligibility depends on various factors, such as the worker's employment status and employment contract duration. As regards sick pay, although its duration does not exceed two weeks in some countries (e.g., Bulgaria, Hungary, and Romania), in many others (e.g., France, Germany, Italy, the Netherlands, and the Nordic countries), it can be up to several months, especially when considering extensions of statutory sick pay durations through collective agreements (EC, 2016). The replacement rates of sick pay also vary widely: from 25% in Slovakia to 100% in Finland (MISSOC, 2016). As for the duration of sickness benefits, it ranges from 6 months in Poland to 3 years in Portugal, and the replacement rates are generally between 50% and 100% of previous earnings (MISSOC, 2016).[9]

Belgium has rather protective labor laws concerning sickness absenteeism. As shown in Chaupain-Guillot and Guillot (2017), based on a correspondence analysis, the level of sickness protection in Belgium is comparable to that of several other Western EU countries, including Austria, Finland, Germany, Luxembourg, and Norway. In line with EU countries' standard practice, Belgium provides rights to sick leave and a "double payment arrangement" based on a mix of sick pay and sickness benefits.

Employees in Belgium have the right to receive their regular salary during 30 calendar days for absences due to sickness.[10] This is the so-called "salaire garanti" rule (i.e., "guaranteed salary" rule). To be eligible for this guaranteed salary, workers need to comply with a number of legal obligations, including, for example, immediately notifying their employer of their sickness status and presenting a medical certificate.[11] Belgium has two sets of provi-

[9] In the case of lump sum benefits (such as in the UK and Malta), the replacement rate is estimated at around 20%.

[10] The sickness protection system in Belgium covers both work and non-work related illnesses and injuries. In the case of work-related illnesses and injuries, additional compensation benefits may be granted (FPS Employment, 2019).

[11] Additional conditions for benefiting from this guaranteed salary differ depending on whether the worker is white- or blue-collar. Regarding white-collar workers, those hired for an unlimited period (permanent contract), for a limited period (fixed-term contract) of at least 3 months, or for a clearly defined task typically requiring an occupation of at least 3 months may claim a guaranteed salary, whereas those hired for a limited period of less than 3 months or for a clearly defined task typically requiring an occupation of less than 3 months must have been employed by the company for at least 1 month without interruption in order to be eligible for a guaranteed salary. As for blue-collar workers, they must have been employed

sions for sick pay: one specific to white-collar workers and one specific to blue-collar workers. Employers are required to pay the full wage (i.e., 100%) during the whole 30 calendar days of guaranteed salary for white-collar workers, whereas they are required to pay 100% of the wage during the first 7 days of absence from work for blue-collar workers, with the exception of the first day, which is not paid at all.[12] From the 8th to the 14th day of sickness absence, employers are required to cover only 85.88% of the regular wage, and from the 15th to the 30th day of sickness absence, only 25.88% of the regular wage for the amount below a certain threshold and 85.88% for the amount above that threshold. The social security system covers the rest in order to guarantee that workers receive the equivalent of their regular wage from the first day (or second, if the "jour de carence" is applicable) to the 30th day.

During the first year of absence following the period covered by the guaranteed salary, employees receive sickness benefits from the social security system.[13] These benefits are equal to 60% of the employee's gross capped wage. Employees who remain sick after one year are eligible for invalidity benefits once their invalidity has been confirmed by a specific board.

As for the level of sickness absence in Belgium, WHO estimates that Belgian employees were absent from work due to sickness for an average of 11.2 days in 2013, a level comparable to the EU-15 average. In other words, in Belgium in 2013, 5.2% of total annual working days were lost due to sickness absences.

The level of sickness protection in Belgium, and more generally in the EU, differs substantially from that in North America. In the US, there is no federal legal requirement to offer paid sick leave. However, the Family and Medical Leave Act (FMLA) provides up to 12 weeks, over a period of 12 months, of unpaid, job-protected leave for the employee in the case of specific medical and family reasons (of the employee or a member of his/her immediate family) (DOL, 2019a).[14] Moreover, several states (e.g., Arizona, Maryland, New

by the company for at least 1 month without interruption in order to be eligible for a guaranteed salary. Note that all white- and blue-collar workers fulfilling these eligibility conditions have the right to claim this guaranteed salary regardless of, for instance, their working time, the size of their company, their sectoral affiliation, being affiliated to a trade union or not, or the type of collective agreement by which the workers are covered.

[12]This is known as "jour de carence". The "jour de carence" was suppressed in 2014. The first day of sickness absence is now fully paid by employers for both white- and blue-collar workers. Yet, as our data cover the period 1999-2007, this "jour de carence" was still applicable.

[13]The maximum duration of sickness benefits is 1 year in Belgium.

[14]To be eligible to take the FMLA leave, employees must have been with their employers for at least 1 year, have worked for at least 1,250 hours over the past 12 months, and work at a location that has at least 50 employees within a 75-mile radius. This FMLA leave could also be used in the case of off-the-job injuries. In the case of on-the-job injuries and work-related illnesses, "workers' compensation", that is, a form of accident insurance paid by the employer, covers workers' medical expenses and provides wage compensation until workers are able to return to work (DOL, 2019b).

Jersey, Oregon, and Massachusetts), counties, and cities have specific laws on that matter. For instance, the city of San Francisco was the first, in November 2006, to guarantee paid sick leave to all its workers. The law grants one hour of paid sick leave time for every 30 hours worked, with a minimum cap at 72 hours in firms with at least 10 employees. Employees in San Francisco can take paid sick leaves for personal illnesses or to care for a sick family member, for preventive care or diagnosis, care or treatment of an existing health condition, or for specified purposes if they are a victim of domestic violence, sexual assault, or stalking (DIR, 2017). In US areas without laws mandating paid sick leave, some employers choose to offer it as a matter of workplace policy or because it is part of employees' contract or required by a collective agreement. Overall, estimates for 2018 suggest that more than 71% of the workers in the US private sector had the possibility to take some paid sick leave (BLS, 2019).

In Canada, the Labour Code specifies that all workers employed in a given company for at least 3 months are eligible for sick leave protection (Government of Canada, 2019a). Sick leave duration may not exceed 17 weeks. Like the FMLA in the US, the Canada Labour Code provides only job security: there is no provision for paid leave of sickness absence. However, some employees may be eligible for compensation under the Employment Insurance Act (Government of Canada, 2019b). Sickness-related provisions also appear in the labor legislation of most Canadian jurisdictions, whereby employers are mandated to provide more favorable sickness protections for their employees, mainly in the form of prolonged sick leave (Rho et al., 2009).

In summary, this comparison at the international level suggests that Canada and especially the US are among the Western countries where employees face the least favorable sickness pay schemes (Rho et al., 2009). From this discussion, it emerges that the potential for sickness absenteeism to affect productivity might depend substantially on the institutional setting. However, the exact outcome remains unsettled. On the one hand, less favorable sickness provisions might be associated with lower sickness absenteeism rates and therefore be less detrimental to firm productivity. On the other hand, these less favorable systems might be associated with higher levels of presenteeism, which, as highlighted before, are also likely to be harmful to firm production. Although Allen (1983) and Zhang et al. (2017) concentrate on the US and Canada, respectively, their results cannot be directly reconciled with ours. First, because these authors consider a global measure of absenteeism, whereas our focus is on sickness absenteeism only. We have discussed earlier how attributing the impact of total absenteeism to sickness absenteeism is likely to be misleading. Second, even if these studies had been focused specifically on sickness absenteeism, our results would hardly have been comparable, because North American sickness protection systems are substantially different from those prevailing in the EU, and particularly in Belgium.

5. Data and measurement

We perform our empirical analysis on a combination of two data sources covering the period 1999-2007.

The first data set, provided by Statistics Belgium, is the Structure of Earnings Survey (SES). It is a longitudinal matched employer-employee data set on a sample of firms that operate in Belgium, employ at least 10 workers, and belong to sectors within sections C to K of the NACE Rev. 1 classification of economic activities.[15] The SES data set contains a wealth of information, provided by the human resources departments of firms, on the characteristics of the firm and the single employees working there. Concerning the firm level, the SES data set reports a variety of information, including the sector of economic activity, the region in which the firm is located, the total number of workers employed in the firm (expressed in full-time equivalents), and the level of collective wage bargaining. Concerning the worker level, the SES data set reports information at the level of the individual worker on variables such as gender, age, education, tenure, type of occupation, the number of hours worked, and the number of hours not worked due to absence. This dataset is particularly relevant for our purpose, as it gives us information at the level of the single worker on the number of hours worked, including overtime hours, and hours not worked due to absence.[16]

The SES data set does not provide financial information on firms. To obtain this source of information, which is necessary for estimating our augmented production function in Equation (1), SES is matched with a different firm-level survey, the Structure of Business Survey (SBS). It is also conducted by Statistics Belgium and provides information on several financial variables, including value added, value of investments in tangible fixed assets, and

[15]The SES data set thus covers the following sectors: mining and quarrying (C); manufacturing (D); electricity, gas, and water supply (E); construction (F); wholesale and retail trade, and repair of motor vehicles, motorcycles, and personal and household goods (G); hotels and restaurants (H); transport, storage, and communication (I); financial intermediation (J); real estate, renting, and business activities (K).

[16]The SES data set is the result of a sophisticated stratified sampling design. The stratification criteria refer to the region (NUTS-groups), sector of economic activity (NACE-groups), and firm size. The sample size in each stratum depends on firm size. Sampling percentages of firms are equal to 10, 50, and 100% when the number of workers is, respectively, lower than 50, between 50 and 99, and over 100. Within the firm, the sampling percentages of employees on which information at the level of the single worker is collected also depend on firm size. The sampling percentages of employees reach 100, 50, 25, 14.3, and 10% when the number of workers in the firm is, respectively, lower than 20, between 20 and 50, between 50 and 99, between 100 and 199, and between 200 and 299. Firms that employ 300 workers or more have to report information for a specific number of employees. This number ranges from 30 (for firms with 300 to 349 workers) to 200 (for firms with 12,000 workers or more). To ensure that firms report information on a representative sample of their workers, they are asked to follow a specific procedure. For a more detailed discussion, see Demunter (2000).

expenditure in intermediate inputs.[17] Statistics Belgium carried out the match between the SES and SBS data sets by using the firm's social security number as firm identifier. We will refer to the resulting matched employer-employee panel data set as "SES-SBS".

In the empirical analysis, we measure the firm's output with (deflated) value added. We measure labor with the total number of workers employed in the firm (expressed in full-time equivalents). We compute capital from flows of (deflated) values of investments in tangible fixed assets by applying a version of the perpetual inventory method described in OECD (2009a). It rests on the idea that capital results from investment flows after correction for retirement and efficiency loss. Following the standard practice, we assume a 5% annual rate of depreciation of capital. We measure intermediate inputs, which we use in the ACF and ACF-FE procedures to proxy the firm's unobserved productivity level, with the (deflated) expenditure in raw materials (including energy), consumables, commodities, services, and other ancillary costs.

The information on the number of hours not worked by the single employees due to absence provided by the SES data set is divided into three categories, which allows constructing a firm-level measure of absenteeism specific to sickness. The first category includes the number of hours entirely paid by the firm but not worked by the employee due to illness or injury. The second category includes the number of hours entirely paid by the firm but not worked by the employee due to reasons other than sickness, such as holidays, compulsory medical examinations, pregnancy tests, absence due to wedding or death of a close family member, etc. The third category collects the number of hours that are not worked by the employee and not paid (or only partially paid) by the firm. This category is heterogeneous and includes the "jour de carence" for blue-collar workers, hours lost by a white-collar worker absent due to sickness beyond 30 days, hours lost by a blue-collar worker absent due to sickness beyond 7 days, hours lost by an employee on sabbatical leave and a woman on maternity leave (note that in Belgium maternity leave is entirely paid by the social security system from the first day).

To compute our measure of firm-level sickness absenteeism, we rely on the first category of hours not worked due to absence, that is, the number of hours entirely paid by the firm but not worked by the employee due to illness or injury. We compute the rate of sickness absenteeism at the firm level, our regressor of interest, as follows. We first add up the number of hours entirely paid by the firm but not worked by the employee due to illness or injury over the employees in the firm in a given year. We thus obtain the total number of hours

[17] Unlike the SES data set, the SBS does not cover the whole financial sector (NACE J), but only two of its sub-sectors: "Other Financial Intermediation" (NACE 652) and "Activities Auxiliary to Financial Intermediation" (NACE 67).

paid by the firm but not worked due to sickness. We then divide this aggregate firm-level figure by the total number of hours worked (including overtime hours) in the firm, where it is obtained by aggregating, at the firm level, the number of hours worked (including overtime hours) by the single employees in the firm in the given year.[18]

This allows us, unlike previous empirical works, to isolate absence certainly due to sickness. Unfortunately, given the structure of our data set, we are not able to compute a total measure of sickness absenteeism. Longer-term sickness absence (i.e., beyond 7 days for blue-collar workers and beyond 30 days for white-collar workers) is mixed with other kinds of absences unrelated to sickness, such as maternity or sabbatical leaves (i.e., absences included in the third category of hours not worked mentioned before). Hence, our measure of firm-level sickness absenteeism should be considered as short-term. Short-term sickness absenteeism constitutes a preponderant share of total sickness absenteeism. For instance, Chimed-Ochir et al. (2019) recently estimated, focusing on Japan, that as much as 90% of total sickness absenteeism only lasts up to 30 days.

Finally, to compute the proportions of workers by gender, age, education, job category, and other workforce characteristics, which we include in our regressions, we divide the total number of hours worked by each category of workers (which we construct as usual by aggregating information from the individual level to the firm level) by the total number of hours worked in the firm. For instance, the share of women in the firm is computed by dividing the total number of hours worked by females over the total number of hours worked in the firm.

Our empirical analysis considers single-plant firms with at least three years of consecutive observations. We restrict the analysis to single-plant firms to make sure that the financial information provided by SBS is at the same level as the workforce-related information provided by SES, otherwise the estimation of the actual impact could be substantially altered. We remove firms with less than three years of consecutive observations for two reasons. First, the ACF-FE (and ACF) estimations need at least two years of consecutive observations to be performed. Second, since those methods are highly demanding in terms of data quality (e.g., ACF-FE only exploits within-firm information and executes complex non-linear estimations), we require an additional year of consecutive observations to get more reliable and precise estimates. Note that requiring one additional year of consecutive observations only

[18] Note that worker-level information on hours worked and hours not worked due to absence reported in the SES data set, on which we construct our measure of firm-level sickness absenteeism, refers to October of any given year. This is a common feature of matched employer-employee data sets (see, for instance, Mion and Opromolla, 2014). We thus implicitly rely on the assumption that October represents a good proxy for the whole year.

results in a small drop in the number of firms observed (i.e., almost all the firms that are observed for two consecutive years are also observed for three consecutive years).[19] Such (unavoidable) restriction on consecutive years of observations leads to the overrepresentation of medium-sized and large firms because the sampling percentages of firms in the SES data set increase with firm size (see Footnote 16). To counterbalance this overrepresentation of medium-sized and large firms, in the empirical analysis, we weighted the observations by the inverse of the firm's employment, expressed as the full-time equivalent number of employees in the firm.[20] Moreover, we removed a few firms (less than 2%) for which public financial control exceeds 50%. The rationale derives from the standard productivity theory and its requirement that prices have to be economically meaningful. Finally, to warrant that workforce-related firm-level variables (e.g., the share of females in the firm) are based on a sufficient number of individual-level observations, we also excluded a small number of firms (less than 1%) that provided information on less than 10 employees.

Our final sample, on which we run the estimation of Equation (1), is the firm-level collapsed version of the cleaned matched employer-employee data set, on which we constructed the firm-level information on workers (e.g., the firm-level rate of sickness absenteeism, the share of females in the firm, etc.). It consists of an unbalanced panel of 5,319 observations for 1,107 firms.

Table 1 reports some descriptive statistics of our sample (weighted by the inverse of firm employment). On average, the firms in our sample employ about 84 workers, produce a value added of slightly more than 8.1 million Euros per year and a gross operating margin of about 4.1 million Euros per year.[21] In the average firm, females represent about 24.9% of the workforce, about three-quarters of the workers do not hold tertiary education, and the vast majority of them (61.9%) are aged between 30 and 49. In the average firm, the vast majority (78.3%) of the workers have been working in that firm for at least 10 years; about one worker in ten is employed part-time, and a few workers (2.8%) have temporary contracts. Most of the workers (57%) are blue-collar workers, such as craft workers or plant and machine operators. The remaining fraction of employees (43%) are white-collar workers: most of them are clerks, professionals, or technicians, and a few have managerial duties. A few firms belong to the mining and quarrying sector (1.4%), most to the manufacturing industry (62.3%), and about one in ten to the construction industry (7.9%). The remaining firms operate in the trade (12%) or services (16.4%) industries. Consistently with the diffusion of small- and

[19] We thoroughly experimented with regressions also including firms with multiple plants and/or firms observed for only two (rather than three) consecutive years, and obtained a broadly consistent picture.

[20] We thank two anonymous referees for having raised this comment.

[21] For simplicity, we will simply say "firms", but actually mean "firm-year observations", as in this case.

medium-sized companies in Belgium, considering weighted observations, most of the firms in our sample are small- or medium-sized: 53.9% of them employ less than 50 workers and 39.5% of them employ between 50 and 250 workers, while only 6.6% employ more than 250 workers.

Table 2 shows descriptive statistics on sickness absenteeism.[22] In our sample, an average of 2% of the total hours worked are lost due to short-term sickness absenteeism. Consistently with the fact that short-term sickness absenteeism represents a great proportion of total sickness absenteeism, our measure of short-term sickness absenteeism represents more than a half of the rate of total sickness absenteeism provided by the official statistics.[23] On average, blue-collar workers are more absent due to sickness (slightly less than twice as much) than white-collar workers, consistently with the fact that blue-collar workers are more subject to injuries and work-related pathologies than white-collar workers. There is no substantial difference in absenteeism rates for high- compared to low-tenure workers. Finally, we observe approximately the same degrees of sickness absenteeism across the categories of firms that we will analyze separately (see Subsection 6.2), namely, industrial *versus* non-industrial firms, low *versus* high capital-intensive firms, and small *versus* medium-sized *versus* large firms.[24] In all these categories of firms, the sickness absenteeism rate oscillates between 0.020 and 0.021, close to the overall average.

6. Results

6.1. The overall impact of sickness absenteeism on productivity

In this section, we present our results from the estimation of Equation (1), that is, for the overall impact of sickness absenteeism on productivity. In Table 3, we report the OLS, FE, ACF, and ACF-FE estimates. As discussed in Section 3, our preferred method is ACF-FE. In all these and the following estimations presented in Subsection 6.2, we add a series of additional inputs to the production process (i.e., included in vector X_{it}) and other controls. The firsts include the proportions of the firm's workforce by gender, age, education, occupation, duration of the work contract (i.e., permanent *versus* fixed-term), working time

[22] As in Table 1, these are weighted by the inverse of firm employment. As shown by Table B.2 in Appendix B, their unweighted counterparts are virtually identical, in line with the observation that levels of sickness absenteeism are almost independent of firm size (see the bottom block of Table 2). Table B.1 in Appendix B reports instead the counterpart of Table 1 but with unweighted observations.

[23] This is not an exact comparison as we compute sickness absenteeism at the firm level and as a percentage of hours lost due to sickness over the total hours worked in the firm, including regular and overtime hours. Official statistics provide a different measure of sickness absence on an individual level and as a percentage of days of absence over the theoretical working days.

[24] Note that statistics for sickness absenteeism rates in small, medium-sized, and large firms are unweighted. This is because we compute sickness absenteeism rates on split samples by firm size in this case.

arrangement (i.e., part-time *versus* full-time), and tenure in the firm. The seconds include dummy indicators for the level of collective wage bargaining and the firm's age, dummy variables for the firm's size, region, and industry, and finally time fixed effects. The FE and ACF-FE estimations also remove firm fixed effects. All standard errors are robust to heteroskedasticity and clustered at the firm level. In ACF and ACF-FE estimations, we compute firm-level cluster-robust bootstrapped standard errors. All these estimations are weighted by the inverse of firm employment.

According to the OLS estimates, the impact of sickness absenteeism on productivity is negative, significant, and equal to -0.637. We know, however, that OLS estimation suffers from a variety of endogeneity problems, which likely hinder the identification of the impact. For example, unobserved characteristics of the firm, such as management quality, may contribute to confounding the estimation. Also, periods of crisis/booms may influence the level of sickness absenteeism. The FE estimation partially addresses such types of problems as it removes unobserved time-invariant heterogeneity (i.e., it accounts for firm fixed effects). According to the more robust FE estimation, the impact of sickness absenteeism is negative, significant, and equal to -0.696, slightly higher in absolute terms than OLS estimates. However, as discussedin Section 3, the FE estimation delivers a consistent estimate of the impact only under rather unrealistic, stringent assumptions. For example, for the FE estimation to give a consistent estimate of the impact, it should hold that sickness absenteeism (and inputs) does not respond to fluctuations in the firm's productivity level. The ACF estimation accounts for a more articulated and realistic picture, according to which inputs and sickness absenteeism can respond to productivity fluctuations (and omitted variable bias can stem from time-varying variables). The ACF estimate of the impact of sickness absenteeism is also negative, significant, and equal to -0.571. The last column of Table 3 reports the ACF-FE estimates. The ACF-FE estimation potentiates the ACF procedure by explicitly removing firm fixed effects. In addition to ensuring that unobserved fixed firm heterogeneity is removed, it also improves the ability of the control function based on intermediate inputs to capture the firm's unobserved productivity level. Our ACF-FE estimates confirm that the impact of sickness absenteeism on productivity is negative and significant. The point estimate of the impact is -0.653. This means that an increase of 1 percentage point in the rate of sickness absenteeism is estimated to decrease productivity by as much as 0.66% (i.e., $(exp^{-0.653*0.010} - 1) * 100$). Equivalently, passing from a zero level of sickness absenteeism to the average level (2%), which means losing 2% of hours worked due to short-term sickness absence, is estimated to decrease productivity by 1.31%.[25]

[25]The ACF-FE estimates of labor and capital elasticities are 0.848 and 0.153, respectively. Such values are

Table C.1 in Appendix C replicates Table 3 with unweighted observations. As one can see, the main result that sickness absenteeism is detrimental to firm productivity is preserved. However, the estimated ACF-FE impact with unweighted observations is significantly lower in magnitude compared to that obtained by weighting observations to account for the over-representation of medium-sized and large firms in our sample. This is coherent with the fact that the overall impact mostly stems from small businesses (see Subsection 6.2), whereby not keeping into account their underrepresentation in the sample results in underestimated coefficients.

In the previous sections, we have stressed how the impact of sickness absenteeism on productivity might be different from that of other types of absenteeism, whereby extending the impact of total absenteeism to that of sickness absenteeism (as in Zhang et al., 2017) could be misleading. Table D.1 in Appendix D carries out this test. First, we show the impact of the firm-level total rate of absenteeism on productivity (first panel of Table D.1). The rate of total absenteeism in the firm is computed as the total number of hours not worked over the total number of hours worked in the firm (including overtime hours). The total number of hours not worked in the firm is obtained by adding up the three types of hours not worked described in Section 5. The impact of total absenteeism on firm productivity is estimated to be small (positive) and largely not significant.

The second panel of Table D.1 shows the differentiated impact of the three types of absenteeism that we can isolate. The first is our measure of (short-term) sickness absenteeism, obtained by adding up the hours lost by employees due to illness or injury and entirely paid by the employers; the second is obtained by adding up the hours lost by employees due to reasons other than sickness and entirely paid by the employers (e.g., holidays, wedding leave, etc.); and the third is obtained by adding up the hours lost by employees which are not paid (or are paid only partially) by the employers. As noted earlier, this last category is heterogeneous and includes absences such as maternity leaves, sabbatical leaves, and long-term sickness absences (plus the "jour de carence"). As one can see from the table, the impact is indeed heterogeneous among the different types of absenteeism. A negative and significant impact is only detected for short-term sickness absenteeism, whereas the second and third types of absenteeism are associated with positive but not significant effects on productivity. Notably, the second type of absenteeism, which is near to a measure of absences for personal reasons, has a relatively large positive impact, though not significant, which might hint at the beneficial effects of more liberal policies on personal leaves. Unfortunately, the fact that

comparable to those found in the literature on the estimation of value-added production functions (see, for example, Van Biesebroeck, 2007). Both estimates are significantly different from zero at any conventional level.

the second and especially third categories mix different types of absences does not allow us to infer the separate effect of specific types of absenteeism such as maternity leaves, personal leaves, or long-term sickness absences. In summary, what emerges is that different types of absences do have different effects on productivity, whereby extending the impact of total absenteeism to sickness absenteeism is indeed problematic.

All in all, we find that sickness absenteeism is, in general, significantly detrimental to firm productivity and that its impact is substantial, which supports our first hypothesis (see Hypothesis 1).

6.2. The diversified impacts of sickness absenteeism on productivity: the role of workforce and firm characteristics

In Section 3, we formulated three additional hypotheses, according to which the impact of sickness absenteeism exacerbates when three circumstances occur. In this subsection, we aim to verify each hypothesis.

According to Hypothesis 2, sickness absenteeism is more detrimental when absent workers have high levels of firm/task-specific (tacit) knowledge. To test this hypothesis, we use the information provided in the SES data set on workers' tenure. Tenure represents a natural proxy for the level of firm/task-specific (tacit) knowledge accumulated by workers. Workers who have been operating in the firm for a long time have a deeper knowledge of the firm and tasks' processes and routines than workers who were more recently hired. In particular, we compute the rate of sickness absenteeism among workers with high tenure (10 years or more) and workers with low tenure (less than 10 years). The results are reported in the first panel of Table 4. According to the ACF-FE estimates[26], sickness absenteeism has a significant impact and is highly detrimental (-1.367 is the point estimate) when absent workers are those with high tenure. Conversely, when absent workers are those with low tenure, the impact on productivity is (positive) small (0.090) and not significant. This result validates Hypothesis 2 and is consistent with the idea that sickness absence is especially problematic when the level of (tacit) knowledge about the firm and tasks' processes and routines is deep, which makes it difficult for the firm to find adequate substitutes, at least in the short run. Conversely, our results are in line with the idea that when the absent workers are those with lower knowledge about the firm and tasks performed, they can more easily be replaced with substitute workers, thus preventing large drops in productivity.

According to Hypothesis 3, sickness absenteeism is more harmful to firms when the

[26] From now on, we only report the ACF-FE results, as ACF-FE is our preferred method. Moreover, note that all these estimations, except for separate regressions by firm size (see below), weight observations by the inverse of firm employment.

work of those absent is highly interconnected with the work of the other employees, as is the case in assembly-line production. Unfortunately, we do not have direct information on whether the firms in our data set have assembly-line production, but we can pinpoint such firms indirectly. To this end, we exploit information on the workers' occupation, the firm's sector, and its degree of capital intensity. Firms with assembly-line production are generally industrial firms (i.e., they produce tangible goods) and high capital-intensive firms (i.e., there are production plants equipped with machinery), and workers in the assembly line are blue-collar workers. We define industrial firms as firms belonging to the following sectors: mining and quarrying, manufacturing, and construction. Conversely, non-industrial firms include firms in the trade and services sectors. Moreover, we classify low and high capital-intensive firms as those whose panel-average ratio between capital and labor (expressed in full-time equivalent employees) is below (above) the median. Finally, we compute the rate of sickness absenteeism among white- and blue-collar workers.

The second panel of Table 4 shows that the impact of sickness absenteeism is negative and significant for both white- and blue-collar workers, but it is substantially higher, in absolute terms, for blue-collar workers (-1.095 for blue-collar workers *versus* -0.414 for white-collar workers). The first panel of Table 5 shows that the negative impact of sickness absenteeism is substantially higher for industrial compared to non-industrial firms, -0.846 for the former *versus* -0.508 for the latter. Finally, the second panel of Table 5 shows that, although low capital-intensive firms are also significantly harmed by sickness absenteeism (-0.277), high capital-intensive companies suffer significant and high productivity drops due to sickness absenteeism (-0.927). In summary, we find that sickness absenteeism is significantly and largely detrimental especially when blue-collar workers are those absent, in industrial firms, and high capital-intensive firms, all situations that can be associated with assembly-line production.

It is nevertheless important to stress that sickness absenteeism is also harmful, though to a lesser extent, when white-collar workers are those absent, in non-industrial firms, and in low capital-intensive companies. Absences of white-collar workers, which include people in managerial or supervisory positions, might harm productivity because it is relatively difficult to find substitute workers for those positions, as the labor pool of workers with the required bundle of skills is limited (Cappelli, 2015). However, one should consider that we focus on short-term sickness absences. Relatively short-term absences of those in high-skilled positions, who often dictate general guidelines for the production processes, are unlikely to represent a significant impediment to the functioning of the production process in the short run, unlike for blue-collar workers, who are directly involved in it. The fact that sickness absenteeism is also harmful to non-industrial and low capital-intensive firms (i.e., typically services firms) is consistent with the idea that substitution opportunities and the possibility to resort to overtime work are also limited in such types of firms (Easton and Rossin, 1997).[27]

Finally, Hypothesis 4 suggests that sickness absenteeism is particularly damaging for small firms, where it is likely more challenging to staff other employees to perform the work of those absent and to hire temporary substitute workers. We test this hypothesis by performing separate regressions on small, medium-sized, and large firms. Following the European Commission classification, we define small firms as those employing less than 50 workers, medium-sized firms as those employing between 50 and 250 workers, and large firms as firms with more than 250 employees. In order to preserve the whole panel for each firm in each split sample, we take the panel average of employees. Unlike the other regression results, these are not weighted by firm size because we consider separate samples. The results support our hypothesis: we find that the impact of sickness absenteeism is negative, significant, and very large in magnitude (the point estimate is -1.361) for small businesses. Although point estimates remain negative for both medium-sized and large firms, the coefficients are not statistically significant at any conventional level in those cases, consistently with the idea that larger firms have more possibilities to resort to overtime and substitute workers.

7. Conclusions

Motivated by the increasing concerns of governments and firms regarding the costs of sickness absence, our paper aimed at consistently measuring the impact of sickness absenteeism on a firm's productivity. To our knowledge, we are the first to examine this issue in the literature, thanks to uniquely detailed matched employer-employee data providing information, at the level of individual workers, on the hours not worked due to illnesses or injuries. This information allowed us to construct a precise measure of firm-level (short-term) sickness absenteeism. In our empirical analysis, we estimated a production function augmented with the level of sickness absenteeism in the firm, and we carefully dealt with endogeneity issues stemming from unobserved heterogeneity and simultaneity by using semiparametric control function methods (i.e., ACF and ACF-FE).

As expected, our results showed that sickness absenteeism has a significant negative impact on a firm's productivity. This impact is large. In general, an increase of 1 percentage point in the rate of sickness absenteeism is estimated to decrease productivity by as much as

[27]Note that the absence of large parts of the financial sector due to SBS data (see Section 5) might affect this result. Firms operating in the financial sector typically employ high-skilled individuals and use teamwork, whereby the negative impact of sickness absenteeism might be relatively higher in this sector. Our estimates for services firms could thus represent a lower bound.

0.66%. Passing from a zero level of short-term sickness absenteeism to the observed average level is estimated to cause productivity losses of 1.31%.

Our results also revealed that sickness absenteeism does not impact all firms in the same manner. We found that the impact varies substantially according to several workforce- and firm-level dimensions. First, we found that the negative impact is particularly significant when high-tenure workers are those absent. This highlights that finding adequate substitutes for absent workers with high levels of firm/task-specific (tacit) knowledge is difficult, and that their absence causes large drops in productivity. Second, we found that the impact of sickness absenteeism is negative, significant, and particularly large in magnitude when blue-collar workers are those absent, in the case of industrial firms, and in high capital-intensive firms: all situations that point to assembly-line production. This finding is consistent with the idea that sickness absenteeism gets more problematic as the firm's production requires a higher degree of interconnection between workers. The impact for white-collar workers' absences remains also negative and significant, in line with the observation that the labor pool for high-skilled workers is relatively limited. Similarly, the impact for non-industrial and low capital-intensive firms (i.e., typically services) remains negative and significant, hinting that substitution opportunities and the possibility to resort to overtime work are also limited in such types of firms. Third, our results showed that sickness absenteeism causes a very large drop in productivity in small companies, whereas larger firms are not significantly exposed to detrimental effects on productivity. This might reflect that smaller firms generally have more difficulty recruiting temporary substitute workers on a short notice and to optimally staff the other workers to perform the work of those absent.

The main policy implication of our findings is that sickness absenteeism not only imposes a direct cost on firms and societies (i.e., wage paid to workers while they are absent, overtime wages, wages to substitute workers, etc.), but it also imposes a significant productivity loss on firms. This finding is particularly relevant considering that productivity growth is a well-known primary source of sustained and sustainable economic growth.

Policy-makers should then invest more resources to effectively improve workers' health and should concentrate their efforts on potentiating educational campaigns on healthy habits and plans for improving workers' well-being in and out of the workplace.

Our results also reveal the incentive for firms to play a fundamental role on this front. Several governments have already implemented laws whereby firms are required to pay sickness benefits to their workers in initial periods of absence, aiming at incentivizing them to keep sickness absenteeism at a low level. Our results thus show that firms have a double incentive: not only is sickness absenteeism costly in terms of labor costs, but also in terms of reduced productivity. Firms should, therefore, invest more in enhancing their workers' health and safety at work, which are key factors to boost productivity (Buhai et al., 2017). Much can be done on this front. For example, firms could consider implementing structured wellness programs and providing higher-quality health insurance to their employees in order to enhance their employees' productivity and reduce sickness absenteeism (Dizioli and Pinheiro, 2016; Gubler et al., 2017).

Similarly, firms could invest more in developing employee-friendly work environments, since stress and mental health problems related to work are also known to be an important determinant of sickness and injuries (Bubonya et al., 2017). For example, they could consider investing more in information and communication technologies in the workplace, as those can significantly contribute to lowering occupational risks and injuries (Askenazy and Caroli, 2010), or contribute to creating cooperative working environments, which have a substantial impact on employees' health conditions (Maclean et al., 2015). Notably, given that sickness absenteeism unfolds with considerable social interaction dynamics, whereby the absence of a worker due to sickness influences other workers' absenteeism, it could be relatively easy for firms to reduce it in an effective way thanks to such multiplicative effects (Dale-Olsen et al., 2015). In this light, firms' investments to ensure better health to their employees represent a win-win strategy. On the one hand, firms could benefit from reduced sickness absenteeism and avoid large productivity drops. On the other hand, employees could benefit from enhanced health, in the first place, and from higher wages stemming from higher productivity, in the second place.

Finally, our findings suggest that managers should consider investing more in their employees' well-being and on-the-job safety programs, especially if they head up firms where sickness absenteeism causes significant productivity penalties: firms with a substantial fraction of the workforce that have in-depth knowledge of the firm and tasks' practices and routines (i.e., workers with high tenure), firms characterized by high degrees of interconnections among workers, and small companies. In addition, policy-makers could consider designing incentives for promoting wellness programs and health insurance specifically for those categories of workers/firms.

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Table 1: **Sample summary statistics: general information**

Variable	**Notes**	**Mean**	**Std. dev.**
Employees	Number of employees expressed in full-time equivalents	83.924	118.738
Value added	1,000 Euros, deflated at 2004 prices	8,129.439	36,257.000
Capital	””	22,892.550	221,231.400
Intermediate inputs	””	17,180.990	171,272.400
Gross operating margin (EBITDA)	””	4,132.393	34,728.700
Share of females		0.249	0.227
Share of young workers	At most 29 years of age	0.223	0.146
Share of prime-age workers	Between 30 and 49 years of age	0.619	0.145
Share of older workers	Over 50 years of age	0.158	0.131
Share of workers with low education	Below High-School Diploma (ISCED 1 and 2)	0.357	0.335
Share of workers with medium education	High School Diploma (ISCED 3 and 4)	0.408	0.293
Share of workers with high education	Over High-School Diploma (ISCED 5, 6, and 7)	0.235	0.253
Share of managers		0.035	0.063
Share of professionals		0.081	0.160
Share of technicians and associate professionals		0.087	0.163
Share of clerks		0.191	0.216
Share of service workers and shop and market sales workers		0.036	0.134
Share of white-collar workers		*0.430*	*0.310*
Share of craft and related trades workers		0.258	0.330
Share of plant and machine operators and assemblers		0.191	0.300
Share of workers involved in elementary occupations		0.121	0.224
Share of blue-collar workers		*0.570*	*0.310*
Share of workers with fixed-term contracts		0.028	0.082
Share of part-time workers	Less than 30 hours per week	0.099	0.123
Share of low-tenure workers	Less than 10 years of tenure	0.217	0.164
Mining and quarrying		0.014	
Manufacturing		0.623	
Construction		0.079	
Trade		0.120	
Services		0.164	
50- employees		0.539	
50-250 employees		0.395	
250+ employees		0.066	
			Observations: 5,319

Source: SES-SBS data set (years: 1999-2007)

All the variables are weighted by the inverse of firm employment (expressed in full-time equivalents).

Table 2: **Sample summary statistics: sickness absenteeism**

Variable	Mean	Std. dev.	Observations
Rate of sickness absenteeism	0.020	0.028	5,319
Rate of sickness absenteeism of low-tenure workers	0.020	0.051	4,764
Rate of sickness absenteeism of high-tenure workers	0.020	0.032	4,764
Rate of sickness absenteeism of white-collar workers	0.014	0.044	4,064
Rate of sickness absenteeism of blue-collar workers	0.024	0.039	4,064
Rate of sickness absenteeism in industrial firms	0.020	0.024	3,885
Rate of sickness absenteeism in non-industrial firms	0.021	0.037	1,434
Rate of sickness absenteeism in low capital-intensive firms	0.020	0.026	2,656
Rate of sickness absenteeism in high capital-intensive firms	0.021	0.031	2,663
Rate of sickness absenteeism in small firms	0.021	0.024	897
Rate of sickness absenteeism in medium-sized firms	0.021	0.030	2,815
Rate of sickness absenteeism in large firms	0.023	0.017	1,607

Source: SES-SBS data set (years: 1999-2007)

All the variables are weighted by the inverse of firm employment (expressed in full-time equivalents), except for the rates of sickness absenteeism in small, medium-sized, and large firms, respectively, which are unweighted.

Blue-collar workers include craft and related trades workers, plant and machine operators and assemblers, and workers involved in elementary occupations. White-collar workers include managers, professionals, technicians and associate professionals, clerks, and service workers and shop and market sales workers. We compute the rates of sickness absenteeism of blue- and white-collar workers only for firms that employ both categories of workers. High-tenure (low-tenure) workers are workers with 10 or more years (less than 10 years) of tenure. We compute the rates of sickness absenteeism of high- and low-tenure workers only for firms that employ both categories of workers. In both cases (i.e., analysis for blue- and white-collar workers and high- and low-tenure workers), we also drop observations that are left with no information on a contiguous year. Industrial firms include firms belonging to mining and quarrying, manufacturing, and construction sectors. Non-industrial firms include firms in the trade and services sectors. We classify low (high) capital-intensive firms as those whose panel-average ratio between capital and labor (expressed in full-time equivalents) is below (above) the median. We define small (medium-sized) (large) firms as those with panel-average employment lower than 50 employees (between 50 and 250 employees) (above 250 employees).

Table 3: **The overall impact of sickness absenteeism on productivity**

	Dependent variable: y_{it}			
Variable	**OLS**	**FE**	**ACF**	**ACF-FE**
l_{it}	0.937***	0.827***	0.913***	0.848***
	(0.033)	(0.041)	(0.037)	(0.043)
k_{it}	0.128***	0.121***	0.152***	0.153***
	(0.016)	(0.032)	(0.028)	(0.035)
Rate of sickness absenteeism	-0.637**	-0.696***	-0.571**	-0.653***
	(0.317)	(0.204)	(0.268)	(0.192)
Share of females	-0.100	-0.059	0.021	-0.029
	(0.089)	(0.098)	(0.055)	(0.083)
Share of young workers	-0.323**	0.138	-0.163*	-0.101
	(0.143)	(0.087)	(0.098)	(0.084)
Share of prime-age workers	-0.281**	-0.111	0.040	-0.018
	(0.135)	(0.074)	(0.100)	(0.087)
Share of workers with low education	-0.255**	0.012	-0.078	0.010
	(0.108)	(0.052)	(0.068)	(0.052)
Share of workers with medium education	-0.185*	0.047	-0.025	0.029
	(0.104)	(0.049)	(0.070)	(0.050)
Share of professionals	-0.518**	-0.060	-0.547*	-0.033
	(0.232)	(0.125)	(0.284)	(0.114)
Share of technicians and associate professionals	-0.971***	-0.041	-0.904***	-0.017
	(0.240)	(0.131)	(0.284)	(0.116)
Share of clerks	-0.770***	-0.101	-0.815***	-0.080
	(0.215)	(0.123)	(0.244)	(0.106)
Share of service workers and shop and market sales workers	-1.296***	-0.045	-1.342***	-0.040
	(0.248)	(0.129)	(0.288)	(0.122)
Share of craft and related trades workers	-1.217***	-0.125	-1.165***	-0.071
	(0.223)	(0.132)	(0.258)	(0.113)
Share of plant and machine operators and assemblers	-1.208***	-0.100	-1.176***	-0.056
	(0.228)	(0.136)	(0.264)	(0.117)
Share of workers involved in elementary occupations	-1.274***	-0.133	-1.261***	-0.069
	(0.233)	(0.137)	(0.279)	(0.118)
Share of workers with fixed-term contracts	0.086	0.014	0.058	0.061
	(0.121)	(0.090)	(0.107)	(0.080)
Share of part-time workers	0.084	0.095	0.524***	0.078
	(0.102)	(0.077)	(0.075)	(0.070)
Share of low-tenure workers	-0.107	0.144***	-0.110*	0.106**
	(0.079)	(0.046)	(0.062)	(0.044)
"In-house" collective agreement	0.173***	0.048***	0.006***	0.001
	(0.031)	(0.018)	(0.001)	(0.001)
Old firm	0.005	0.018	-0.008***	0.001
	(0.039)	(0.032)	(0.003)	(0.003)
Year dummies	yes	yes	yes	yes
Size dummies	yes	yes	yes	yes
Region dummies	yes	-	yes	-
Industry dummies	yes	-	yes	-
Firm fixed effects	no	yes	no	yes
				Observations: 5,319

Source: SBS-SES data set (years: 1999-2007)

*All the estimations are weighted by the inverse of firm employment (expressed in full-time equivalents). Standard errors, reported in parentheses, are robust and clustered at the firm level. In ACF and ACF-FE estimations, we compute firm-level cluster-robust bootstrapped standard errors. ***, **, and * denote, respectively, the 1%, 5%, and 10% significance level. The reference group for the age distribution is the share of older workers; for the education distribution, it is the share of workers with high education; for the occupation distribution, it is the share of managers. "Old firm" is a dummy variable indicating that the firm is at least 10 years old. Size dummies consist of 3 dummies, 1 for each size class as of Table 1; region dummies consist of 3 dummies, 1 for each administrative region in Belgium (Brussels-Capital, Flanders, and Wallonia); industry dummies account for 146 dummies, 1 for each 3-digit NACE Rev 1.1 industry.*

Table 4: **The impact depending on the categories of workers**

Rate of sickness absenteeism of low-tenure workers	0.090	(0.078)
Rate of sickness absenteeism of high-tenure workers	-1.367***	(0.203)
	Observations: 4,764	
Rate of sickness absenteeism of white-collar workers	-0.414***	(0.132)
Rate of sickness absenteeism of blue-collar workers	-1.095***	(0.250)
	Observations: 4,064	

Source: SBS-SES data set (years: 1999-2007)
*Estimation method: ACF-FE. All the estimations are weighted by the inverse of firm employment (expressed in full-time equivalents). In parentheses, firm-level cluster-robust bootstrapped standard errors. ***, **, and * denote, respectively, the 1%, 5%, and 10% significance level. These estimates include the same set of controls as in Table 3. For the rest, see the footnotes of Table 3 and Table 2.*

Table 5: **The impact depending on the categories of firms**

Industrial firms versus *non-industrial firms*			
Impact of sickness absenteeism on industrial firms	-0.846**	(0.355)	[3,885]
Impact of sickness absenteeism on non-industrial firms	-0.508*	(0.302)	[1,434]
Low capital-intensive firms versus *high capital-intensive firms*			
Impact of sickness absenteeism on low capital-intensive firms	-0.277**	(0.140)	[2,656]
Impact of sickness absenteeism on high capital-intensive firms	-0.927*	(0.496)	[2,663]
Small versus *medium-sized* versus *large firms*			
Impact of sickness absenteeism on small firms	-1.361***	(0.337)	[897]
Impact of sickness absenteeism on medium-sized firms	-0.162	(0.200)	[2,815]
Impact of sickness absenteeism on large firms	-0.008	(0.376)	[1,607]

Source: SBS-SES data set (years: 1999-2007)
*Estimation method: ACF-FE. All the estimations are weighted by the inverse of firm employment (expressed in full-time equivalents), except for estimations by firm size (i.e., on small, medium-sized, and large firms), which are unweighted. In parentheses, firm-level cluster-robust bootstrapped standard errors. In square brackets, the number of observations of the different sub-samples. ***, **, and * denote, respectively, the 1%, 5%, and 10% significance level. These estimates include the same set of controls as in Table 3. For the rest, see the footnotes of Table 3 and Table 2.*

Appendices

A. The empirical framework and the ACF and ACF-FE methods

It is noteworthy to stress, as a foreword, that the ACF and ACF-FE methods are estimation procedures specifically designed for estimating firm-level production functions. These methods belong to the literature on CFEs of firm-level production functions, initiated a few decades ago with the work of OP, and are based on the approximation of unobserved productivity levels through a function of observables, called "control function". These methods rest on structural econometric models and are constructed upon a number of assumptions, discussed in detail in Ackerberg et al. (2015) (ACF) and Lee et al. (2019) (ACF-FE). Within these econometric models, the researcher can adapt production functions augmented with any variable of interest, sickness absenteeism in our case. As regards the assumptions, the researcher has a relatively low degree of flexibility within CFEs, which is mainly limited to the definition of timing assumptions (e.g., timing in the choice of labor and capital inputs and timing in the realization of the variable of interest). This being said, we now present a discussion of our empirical framework in the context of ACF and ACF-FE estimations. For details on the underlying assumptions - which we summarize here - and their implications, we refer the reader to Ackerberg et al. (2015) and Lee et al. (2019).

As specified in Section 3, the augmented production function that we estimate is the following (for the sake of simplicity, we omit the term including basic control dummies C_{it}):

$$y_{it} = \alpha + \beta_l l_{it} + \beta_k k_{it} + \theta SABS_{it} + \gamma X_{it} + \omega_{it} + \epsilon_{it}. \tag{A.1}$$

First, it is assumed that the firm's information set at t, I_{it}, includes current and past productivity levels, $\{\omega_{i\tau}\}_{\tau=0}^{t}$, but not future productivity levels, $\{\omega_{i\tau}\}_{\tau=t+1}^{\infty}$. Furthermore, it is assumed that the transitory shock, ϵ_{it}, is not predictable by the firm (i.e., $E[\epsilon_{it}|I_{it} = 0]$).

Second, it is assumed that the unobserved productivity level, ω_{it}, evolves according to the distribution:

$$p(\omega_{it+1}|I_{it}) = p(\omega_{it+1}|\omega_{it}), \tag{A.2}$$

which is known to the firm. Equation (A.2) expresses that the productivity level evolves according to a first-order Markov process.

These two assumptions imply that it is possible to decompose ω_{it} into its conditional expectation at $t-1$ and an innovation term:

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

where, by construction, $E[\xi_{it}|I_{it-1}] = 0$. Hence, $g(\omega_{it-1})$ is that part of ω_{it} that the firm can predict at $t-1$, whereas ξ_{it} is the innovation in ω_{it}, observed by the firm at t and, by construction, not predictable at $t-1$. In practice, firms observe ω_{it} at t and construct expectations on ω_{it} at $t-1$ by using $g(\cdot)$.

An example helps to clarify the point. Suppose that the firm is experiencing a period of productivity boom, that is, a series of positive productivity shocks. This is compatible, for instance, with technological progress introduced in the firm (e.g., adoption of robotics and artificial intelligence). The set of assumptions outlined above imply that the firm knows the past and current productivity enhancements it is experiencing. It also implies that the firm is able to predict, with a degree of error, the next period's productivity level based (solely) on the current productivity level.[A.1]

Third, it is assumed that firms accumulate capital according to:

$$k_{it} = \kappa(k_{it-1}, i_{it-1}),$$

where investments i_{it-1} are chosen at $t-1$. This implies that the firm decides upon the level of capital to use at t one period earlier, at $t-1$ (i.e., $k_{it} \in I_{it-1}$). This assumption entails that it takes a full period for new capital to be ordered, delivered, and installed. Moreover, it implies that capital has dynamic implications, in the sense that the firm's choice of capital for period t has an impact on the firm's future profits. We assume that the firm decides upon the level of labor to use at t in the same period, at t.[A.2] Consistently with the idea

[A.1] Note that the literature on CFEs of production functions initiated by OP, including LP and ACF, has always assumed a first-order Markov process in the unobserved productivity level, whereby the ω_{it} process can be treated completely nonparametrically. On the one hand, this represents a substantial improvement compared to the literature on the dynamic-panel estimation of production functions (e.g., DIFF-GMM or SYSTEM-GMM methods developed by Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 2000, 1998), which instead relies on the linearity of the ω_{it} process. On the other hand, the first-order Markov process excludes that current productivity levels depend on past productivity levels other than that at $t-1$ (i.e., ω_{t-2}, ω_{t-3}, and so on). As explained in Ackerberg et al. (2007), although it is in principle possible to accommodate unobserved productivity to follow a higher-order Markov process, implementing this is not straightforward in the context of production functions, as it requires using as many proxy variables as the order of the Markov process. Until now, the literature on CFEs of production functions has proposed two different variables in order to proxy for the unobserved productivity levels: investments and intermediate inputs. As discussed in Section 3, since the work by LP, the use of investments as a proxy variable has been questioned and abandoned due to truncation problems and lumpiness, and intermediate inputs started to be adopted. To the best of our knowledge, other possibilities for proxy variables have not been advanced so far in the literature, and (consequently) modeling productivity with higher-order Markov processes is not currently pursued either.

[A.2] We stick to the common practice of assuming that labor is a variable input (e.g., see Parrotta and Pozzoli, 2012; Vandenberghe, 2012; Vandenberghe et al., 2013). The ACF (and ACF-FE) frameworks are also consistent with assuming that labor at t is chosen, as capital, one period earlier, thereby allowing it to have dynamic implications. While this assumption might be reasonable in the presence of significant labor that employees' health, and thus sickness (i.e., illness- and injury-related) absenteeism, can respond immediately to productivity shocks, we assume that sickness absenteeism at t is also determined at t.[A.3] Finally, consistently with the assumption that the amount of labor at t is determined at t, we assume that the other inputs of the augmented production function at t - those in vector X_{it}, collecting variables on workforce composition - are also determined at t.

Fourth, it is assumed that the firm's demand for intermediate inputs, m_{it}, is a function of labor, capital, sickness absenteeism, other inputs X_{it}, and the firm's unobserved productivity level:

$$m_{it} = f(l_{it}, k_{it}, SABS_{it}, X_{it}, \omega_{it}) \tag{A.3}$$

Lastly, it is assumed that the function in (A.3) is strictly increasing in ω_{it}. Intuitively, this means that, conditional on labor, capital, sickness absenteeism, and other inputs X_{it}, the higher the unobserved productivity level, the larger the demand for intermediate inputs.

At this point, ACF outline a two-step estimation method. Given the assumptions discussed above, f can be inverted out to deliver an expression of ω_{it}, which is unobservable, as a function of l_{it}, k_{it}, $SABS_{it}$, X_{it}, and m_{it}, which are instead observable:

$$\omega_{it} = f^{-1}(l_{it}, k_{it}, SABS_{it}, X_{it}, m_{it}).$$

The inverted intermediate input demand function $f^{-1}(\cdot)$ is the key to CFEs: it allows to "control" for the unobserved productivity level once plugged into the production function. Hence, substituting $f^{-1}(\cdot)$ into Equation (A.1) results in the following first-stage equation:

$$\begin{aligned} y_{it} = \alpha + \beta_l l_{it} + \beta_k k_{it} + \theta SABS_{it} + \gamma X_{it} + f^{-1}(l_{it}, k_{it}, SABS_{it}, X_{it}, m_{it}) + \epsilon_{it} \\ = \Phi(l_{it}, k_{it}, SABS_{it}, X_{it}, m_{it}) + \epsilon_{it} \end{aligned} \tag{A.4}$$

As it is common in the literature, we proxy the function $f^{-1}(\cdot)$ with a third-order polynomial in l_{it}, k_{it}, $SABS_{it}$, X_{it}, and m_{it} (Ackerberg et al., 2015, p. 2419). The parameters β_l, β_k, θ, and γ are clearly not identified at this stage and are subsumed into $\Phi(l_{it}, k_{it}, SABS_{it}, X_{it}, m_{it}) = \alpha + \beta_l l_{it} + \beta_k k_{it} + \theta SABS_{it} + \gamma X_{it} + \omega_{it}$. However, the estimation of (A.4) produces an estimate $\tilde{\Phi}(l_{it}, k_{it}, SABS_{it}, X_{it}, m_{it})$ of $\Phi(l_{it}, k_{it}, SABS_{it}, X_{it}, m_{it})$.[A.4]

market rigidities, it is potentially a strong assumption that could significantly bias the estimates (Ackerberg et al., 2015, p. 2430).

[A.3] From this point onward, the ACF (and ACF-FE) methods are adapted to our augmented production function in Equation (A.1). Similar discussions, but with different variables of interests, can be found, for instance, in Parrotta and Pozzoli (2012) or Konings and Vanormelingen (2015).

[A.4] Note that these are just the predicted values from the regression in Equation (A.4).

Given guesses of β_l, β_k, θ, and γ, respectively denoted β_l^*, β_k^*, θ^*, and γ^*, it is possible to recover implied ω_{it}, $\tilde{\omega}_{it}(\beta_l^*, \beta_k^*, \theta^*, \gamma^*)$[A.5], as:

$$\tilde{\omega}_{it}(\beta_l^*, \beta_k^*, \theta^*, \gamma^*) = \tilde{\Phi}(l_{it}, k_{it}, SABS_{it}, X_{it}, m_{it}) - \beta_l^* l_{it} - \beta_k^* k_{it} - \theta^* SABS_{it} - \gamma^* X_{it}. \quad \text{(A.5)}$$

As ω_{it} is assumed to follow a first-order Markov process (i.e., $\omega_{it} = g(\omega_{it-1}) + \xi_{it}$) and given $\tilde{\omega}_{it}(\beta_l^*, \beta_k^*, \theta^*, \gamma^*)$, it is possible to compute the implied innovations, $\tilde{\xi}_{it}(\beta_l^*, \beta_k^*, \theta^*, \gamma^*)$, as the residuals from a regression of $\tilde{\omega}_{it}(\beta_l^*, \beta_k^*, \theta^*, \gamma^*)$ on $g(\tilde{\omega}_{it-1}(\beta_l^*, \beta_k^*, \theta^*, \gamma^*))$. Following the standard practice, we proxy the function $g(\cdot)$ with a third-order polynomial in $\tilde{\omega}_{it-1}(\beta_l^*, \beta_k^*, \theta^*, \gamma^*)$ (Lee et al., 2019, p. 82). The second step of the procedure now recovers the parameters of interest by evaluating the sample analogues of the moment conditions stemming from the timing assumptions previously stated:

$$\begin{aligned}
&\frac{1}{N}\frac{1}{T}\sum_i \sum_t \tilde{\xi}_{it}(\beta_l^*, \beta_k^*, \theta^*, \gamma^*) k_{it} = 0 \\
&\frac{1}{N}\frac{1}{T}\sum_i \sum_t \tilde{\xi}_{it}(\beta_l^*, \beta_k^*, \theta^*, \gamma^*) l_{it-1} = 0 \\
&\frac{1}{N}\frac{1}{T}\sum_i \sum_t \tilde{\xi}_{it}(\beta_l^*, \beta_k^*, \theta^*, \gamma^*) SABS_{it-1} = 0 \\
&\frac{1}{N}\frac{1}{T}\sum_i \sum_t \tilde{\xi}_{it}(\beta_l^*, \beta_k^*, \theta^*, \gamma^*) X_{it-1} = 0.
\end{aligned} \quad \text{(A.6)}$$

The search over β_l^*, β_k^*, θ^*, γ^* continues until $\tilde{\beta}_l$, $\tilde{\beta}_k$, $\tilde{\theta}$, and $\tilde{\gamma}$ are found that satisfy Equation (A.6). These are the ACF estimates of β_l, β_k, θ, and γ.

The ACF-FE estimator involves only a minimal modification to the standard ACF method, which can be outlined as follows. All the assumptions of ACF are maintained, except that the assumption on the stochastic process regulating unobserved productivity is generalized in the ACF-FE setting. In particular, unobserved productivity ω_{it} is assumed to follow a first-order Markov process conditional on a time-invariant random variable η_i:

$$\omega_{it} = E[\omega_{it}|\omega_{it-1}, \eta_i] + \xi_{it}, \quad \text{(A.7)}$$

where $E[\xi_{it}|\omega_{it-1}, \eta_i] = 0$ and $E[\epsilon_{it}|\eta_i = 0]$. In particular, Lee et al. (2019) consider a version of Equation (A.7) where $E[\omega_{it}|\omega_{it-1}, \eta_i] = \eta_i + g(\omega_{it-1})$, thus giving:

$$\omega_{it} = \eta_i + g(\omega_{it-1}) + \xi_{it} \quad \text{(A.8)}$$

[A.5] They also include the constant term α, which eventually does not matter.

Under the above specification of ω_{it}, the first step of the ACF-FE procedure is the same as in ACF except for adding the fixed-term effect η_i. It is still possible to estimate $\Phi(\cdot)$ from the analogue of Equation (A.4) with added fixed effects. At the second stage, it is possible to estimate β_l, β_k, θ, γ proceeding as before but with the inclusion of η_i in the stochastic process of the unobserved productivity level as defined in Equation (A.8), thereby recovering implied ω_{it} as in (A.5) and then implied ξ_{it} as the residuals from a fixed effects regression of $\tilde{\omega}_{it}$ on $g(\tilde{\omega}_{it-1})$, with $g(\cdot)$ approximated with a third-order polynomial (Lee et al., 2019, p. 87).

B. Unweighted descriptive statistics

Table B.1: **Sample summary statistics: general information - unweighted**

Variable	**Notes**	**Mean**	**Std. dev.**
Employees	Number of employees expressed in full-time equivalents	243.767	391.294
Value added	1,000 Euros, deflated at 2004 prices	20,746.710	56,121.990
Capital	””	48,558.250	272,734.300
Intermediate inputs	””	54,433.490	417,053.300
Gross operating margin (EBITDA)	””	8,258.574	42,748.430
Share of females		0.236	0.221
Share of young workers	At most 29 years of age	0.223	0.138
Share of prime-age workers	Between 30 and 49 years of age	0.622	0.135
Share of older workers	Over 50 years of age	0.155	0.119
Share of workers with low education	Below High-School Diploma (ISCED 1 and 2)	0.357	0.319
Share of workers with medium education	High School Diploma (ISCED 3 and 4)	0.404	0.281
Share of workers with high education	Over High-School Diploma (ISCED 5, 6, and 7)	0.239	0.245
Share of managers		0.035	0.061
Share of professionals		0.094	0.168
Share of technicians and associate professionals		0.078	0.143
Share of clerks		0.167	0.190
Share of service workers and shop and market sales workers		0.033	0.126
Share of white-collar workers		*0.407*	*0.310*
Share of craft and related trades workers		0.258	0.324
Share of plant and machine operators and assemblers		0.236	0.310
Share of workers involved in elementary occupations		0.098	0.202
Share of blue-collar workers		*0.593*	*0.310*
Share of workers with fixed-term contracts		0.037	0.093
Share of part-time workers	Less than 30 hours per week	0.100	0.125
Share of low-tenure workers	Less than 10 years of tenure	0.208	0.162
Mining and quarrying		0.008	
Manufacturing		0.609	
Construction		0.113	
Trade		0.096	
Services		0.174	
50- employees		0.172	
50-250 employees		0.529	
250+ employees		0.299	
			Observations: 5,319

Source: SES-SBS data set (years: 1999-2007)

Table B.2: **Sample summary statistics: sickness absenteeism - unweighted**

Variable	**Mean**	**Std. dev.**	**Observations**
Rate of sickness absenteeism	0.021	0.026	5,319
Rate of sickness absenteeism of low-tenure workers	0.022	0.053	4,764
Rate of sickness absenteeism of high-tenure workers	0.021	0.029	4,764
Rate of sickness absenteeism of white-collar workers	0.014	0.041	4,064
Rate of sickness absenteeism of blue-collar workers	0.026	0.034	4,064
Rate of sickness absenteeism in industrial firms	0.021	0.023	3,885
Rate of sickness absenteeism in non-industrial firms	0.021	0.032	1,434
Rate of sickness absenteeism in low capital-intensive firms	0.021	0.024	2,656
Rate of sickness absenteeism in high capital-intensive firms	0.022	0.027	2,663

Source: SES-SBS data set (years: 1999-2007)
For information on categorizations (e.g., low- versus *high-tenure workers, industrial* versus *non-industrial firms, etc.), see the footnotes of Table 2.*

C. Unweighted regressions

Table C.1: **The overall impact of sickness absenteeism on productivity - unweighted**

Dependent variable: y_{it}				
Variable	**OLS**	**FE**	**ACF**	**ACF-FE**
l_{it}	0.974***	0.903***	0.856***	0.830***
	(0.025)	(0.031)	(0.035)	(0.032)
k_{it}	0.113***	0.066***	0.173***	0.124***
	(0.014)	(0.018)	(0.027)	(0.023)
Rate of sickness absenteeism	-0.388	-0.450***	-0.276*	-0.183**
	(0.309)	(0.171)	(0.158)	(0.089)
Workforce controls	yes	yes	yes	yes
Firm controls	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes
Size dummies	yes	yes	yes	yes
Region dummies	yes	-	yes	-
Industry dummies	yes	-	yes	-
Firm fixed effects	no	yes	no	yes
				Observations: 5,319

Source: SBS-SES data set (years: 1999-2007)
*Standard errors, reported in parentheses, are robust and clustered at the firm level. In ACF and ACF-FE estimations, we compute firm-level cluster-robust bootstrapped standard errors. ***, **, and * denote, respectively, the 1%, 5%, and 10% significance level. Controls are the same as those in Table 3. For the rest, see the footnotes of Table 3.*

D. Total absenteeism and different categories of absenteeism

Table D.1: **The impact of total absenteeism and different categories of absenteeism**

			Mean	Std. dev.
Rate of total absenteeism	0.040	(0.078)	0.135	0.131
Rate of sickness absenteeism	-0.671***	(0.149)	0.021	0.026
Rate of absenteeism type 1	0.297	(0.314)	0.037	0.041
Rate of absenteeism type 2	0.050	(0.094)	0.077	0.125
			Observations: 5,319	

Source: SBS-SES data set (years: 1999-2007)

*Estimation method: ACF-FE. All the estimations are weighted by the inverse of firm employment (expressed in full-time equivalents). In parentheses, firm-level cluster-robust bootstrapped standard errors. ***, **, and * denote, respectively, the 1%, 5%, and 10% significance level. These estimates include the same set of controls as in Table 3. For the rest, see the footnotes of Table 3. The category "absenteeism type 1" collects hours lost due to reasons other than sickness and totally paid by the firm, such as holidays for employees, compulsory medical examinations, public holidays, pregnancy tests, absences due to wedding or death of a close family member, etc. The category "absenteeism type 2" groups hours lost but not paid (or only partially paid) by the firm. This category includes the "jour de carence" for blue-collar workers, hours lost by white-collar workers absent due to sickness beyond 30 days, hours lost by blue-collar workers absent due to sickness beyond 7 days, hours lost by employees on sabbatical leave and women on maternity leave. Sickness absenteeism, absenteeism type 1, and absenteeism type 2 add up to total absenteeism.*