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DISCUSSION PAPER SERIES

IZA DP No. 14432

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MAY 2021

ISSN: 2365-9793

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ABSTRACT

Can You Teach an Old Dog New Tricks? New Evidence on the Impact of Tenure on Productivity

In this paper, we explore the impact of workers' tenure on firm productivity, using rich longitudinal matched employer-employee data on private Belgian firms. We estimate a production function augmented with a firm-level measure of tenure. We deal with endogeneity, which arises from unobserved firm heterogeneity and reverse causality, by applying a modified version of Ackerberg et al.'s (2015) control function method, which explicitly removes firm fixed effects. Consistently with recent theoretical predictions, we find that tenure exhibits an inverted-U-shaped relationship with respect to productivity. The existence of decreasing marginal returns to tenure is corroborated in our analysis on the tenure composition of the workforce. We also find that the impact of tenure differs widely across workforce and firm dimensions. Tenure is particularly beneficial for productivity in contexts characterized by a certain degree of routineness and lower job complexity. Along the same lines, our findings indicate that tenure exerts stronger (positive) impacts in industrial and high capital-intensive firms, as well as in firms less reliant on knowledge- and ICT-intensive processes.

JEL Classification: D24, M59

Keywords: tenure, firm productivity, semiparametric methods to estimate production functions, longitudinal matched employer-employee data

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1. Introduction

The increasing labor market flexibilization pressure and rising trends of atypical work appear to question the relevance of seniority and stability in the employment relationship. Nonetheless, standard employment (i.e., permanent, full time and subject to regulation) remains a widespread and dominant employment form, particularly in European countries (Eurofund, 2020). At the same time, an employee's length of service (or tenure[1]) with an employer is still a significant structural factor within the employment relationship (Eurofund, 2019). In the OECD aggregate, the average number of years spent with the same employer was about 9.5 years in 2019 and 9.2 years during the 2000-2019 period, albeit with differences across countries. Tenure, which is often considered a source of inefficiency, as it may discourage employees' efforts, drives up wages and erodes competitiveness (Conrad, 2010), also arguably represents an important incentive for both employers and employees to invest in high-quality employment and to spur employees' performance (Eurofund, 2019). However, persisting labor market rigidities, combined with recent megatrends, constantly challenge the dynamism of organizations. Strict employment protection legislation (EPL) may hamper organizational changes and have potential repercussions on the long-term economic development and competitiveness of firms (Berglund Furåker, 2016; Eurofund, 2015). Changing fertility, life expectancy and migration dynamics are expected to lead to a dramatic population aging over the coming decades, which in turn will result in a higher labor force participation of older workers (European Commission, 2021; Bryson et al., 2020). Fast-changing environments and accelerating technological changes are likely to engender higher occupational churning and job displacement, as a result of skill obsolescence and task automation (OECD, 2019a). In such a setting, striking an ideal balance between employee attraction and retention has become ever more essential to achieve organizational success.

In this paper, we explore the relationship between tenure and firm performance. A workers' seniority with an employer may *a priori* be associated with a boon to performance. As a relevant determinant of employment stability, tenure may entail a sense of job security, thereby resulting in higher organizational commitment and engagement (Getahun Asfaw and Chang, 2019; Furåker and Berglund, 2014; Auer et al., 2005). In addition, a long tenure usually underpins extensive tacit and firm-specific knowledge (Polanyi, 1966;1958; Becker, 1964) as well as a better fit with the organizational environment, its values, norms and procedures (Mitchell et al, 2001; Schneider, 1987). Nevertheless, tenure-related benefits might not necessarily persist over time. The natural existence of learning curves implies that the amount of acquirable organizational knowledge is set

[1] The literature typically distinguishes between 'organizational tenure' (i.e., the length of employment in a given firm) and 'job tenure' (i.e., the length of employment in one position) (Ng and Feldman, 2010). In this article, we focus on the former dimension, and we use the term 'tenure' to define the length of time an employee has been with the same employer.

to reach a cap as tenure progresses (Shaw and Lazear, 2008). In this respect, the characteristics of the workforce and the firm may be relevant moderators. The workers' ages, the degree of task routineness, the level of job complexity, together with the production process features (e.g., degree of knowledge-intensity), may affect the steepness\length of the curve. Accordingly, long-tenured employees might progressively exhibit a reduced performance potential, due to caps on learning, a decline in cognitive and physical abilities, increased boredom, a loss of motivation, lower engagement, and reduced versatility. Furthermore, tenure involves significant sunk costs (e.g., time invested in firm-specific training; seniority-based pay) which in turn may lead workers to feel the need to stay with a given organization – with consequent detrimental effects on their exerted effort and performance (Cohen, 1993; Becker, 1960; Meyer et al., 1989). Overall, these arguments appear to dispel the notion of the enduring performing potential of tenured workers and emphasize the existence of a certain curvilinearity (i.e., an inverted-U-shaped relationship) between tenure and performance. Hence, once an optimal level has been attained, decreasing marginal returns to tenure might occur. A thorough examination of such a nexus is therefore of paramount importance.

We contribute to this debate, since we aim to reconcile the different strands of literature, by performing a robust empirical assessment of the impact of workers' tenure on firm performance. We focus on firm productivity, as it is widely recognized as the ultimate engine of growth in today's global economy (OECD, 2015). It is thus essential for researchers in economic disciplines to understand what factors influence it, and in what way. In recent years, a small but compelling strand of literature has investigated how several labor-related issues affect productivity (e.g., Grinza 2020; Grinza and Rycx, 2020; Devicienti et al., 2018; Giuliano et al., 2017; Vandenberghe, 2013). However, there is no recent and robust empirical evidence on the impact of tenure on productivity. This may be attributable to a lack of suitable data, as a robust investigation of employees' retention on productivity requires data structures that provide both worker- and firm-level information. For this purpose, matched employer-employee data, which allow detailed firm and workforce characteristics (including tenure) to be constructed, have only been available for a relatively short time (Card et al., 2014; Abowd and Kramarz, 1999).

A number of papers have focused on the tenure-performance nexus. They differ across the performance, data and method dimensions. Most studies focus on subjective job performance measures (e.g., supervisors' evaluations and/or workers' self-assessments), which are likely to suffer from well-known biases (Fehrenbacher et al. 2018; Sturman, 2003; Bommer et al., 1995). In addition, the current empirical works rely either on meta-analyses (Ng and Feldman, 2010; Sturman, 2003), country data (Auer et al., 2005) or sector-level data (Blakemore and Hoffman, 1989), single-firm case studies (Steffens et al., 2014; Flabbi and Ichino, 2001; Medoff and Abraham, 1981; 1980), or longitudinal field studies (Uppal et al., 2017), thereby just providing aggregate evidence or lacking generalizability. Finally, the existing contributions rely on estimation methods that do not account for unobserved firm heterogeneity and potential simultaneity issues.

Our paper adds to the literature in four ways. First, we focus on an objective measure of firm performance (i.e., productivity). Second, we look at the potentially curvilinear (i.e., inverted-U-shaped) relationship between tenure and productivity, by also complementing this estimation with an investigation on the tenure composition of the workforce (i.e., workers' shares for different tenure levels). We thus examine how changes in the proportions of low-tenured workers (up to 5 years), medium- (between 6 and 11 years), and high-tenured (12 years or more) workers affect productivity. This choice allows us to unveil any potentially heterogeneous patterns on the labor market. Third, we explore any possible moderating effects on our relationship of interest to assess whether, and to what extent, the impact of tenure on productivity may be differentially affected by relevant workforce and firm dimensions. Finally, we apply a robust estimation framework to a rich, longitudinal matched employer-employee data set pertaining to private Belgian firms over the 2005-2016 period.

Detailed information on the workers' length of firm-specific employment (i.e., number of years in a given firm) is used to compute a precise firm-level measure of tenure for a given year. Our data provide accurate balance-sheet information for the estimation of the production function and allow to control for a wide range of worker's (e.g., education, age, occupation) and firm characteristics (e.g., size, age, industry), while removing any unobserved fixed firm heterogeneity. The matched employer-employee nature of our data also offers the advantage of being able to obtain measures of firm-level tenure for different groups of workers (e.g., low-skilled *versus* high-skilled; routine *versus* non-routine). In our empirical analysis, we estimate production functions, augmented with firm-level measures of tenure, by adopting a modified version of the semiparametric control function approach designed by Ackerberg et al. (2015), and recently further developed by Lee et al. (2019), which controls for reverse causality and explicitly removes firm fixed effects. To the best of our knowledge, this paper is the first to provide empirical evidence on (various aspects of) the tenure-productivity relationship using detailed longitudinal matched employer-employee data and applying robust methodological techniques.

In line with the most recent theoretical predictions, our main result is that tenure does in fact exhibit a curvilinear relationship (i.e., inverted-U-shaped) with respect to productivity. The impact of tenure on productivity is thus positive (albeit with decreasing marginal returns) up to a certain point, after which it becomes negative. The inflection point of the relationship occurs at around 23 years of tenure in a firm, thus implying that any additional years of service with the same employer exert a positive (negative) impact on firm productivity before (after) that threshold. Our complementary analysis on the tenure composition of the workforce corroborates the existence of decreasing returns to tenure. We also find that the impact of tenure differs widely according to workforce and firm characteristics. Tenure is particularly beneficial for productivity in contexts characterized by a certain degree of routineness and lower job complexity. Consistently, our findings indicate that tenure is more relevant for performance in industrial and high capital-intensive firms, as well as in firms that rely less on knowledge- and ICT-intensive processes.

These results have pervasive policy implications, which point to a careful consideration of the role played by tenure in the designing and implementation of effective personnel strategies. In this regard, workforce and sectoral specificities appear to matter a great deal. Moreover, these results are particularly relevant, given the widespread (and often institutionalized) practice across firms of valuing long tenure using seniority-based pay schemes (Eurofund, 2019; Lazear, 1981;1979). Tenure, together with a steep wage structure, serves a dual purpose: it allows firms to invest in their workers over time, and induces the latter to remain with their employer in the long term (Storm and Naastepad, 2007; Auer et al., 2005). Nevertheless, a system that boundlessly links tenure to remuneration may create a 'golden cage' for low-level performers, but not be able to retain high-level performers (Baeten et al., 2018). Similarly, seniority-linked pay entitlements might entail perceptions of unequal treatment (due to unequal pay for the same work done by equally qualified and competent individuals – Eurofund, 2019), thereby abating the employees' morale and performance. Hence, the results of this paper also provide crucial insights, for social partners and policy makers alike, to assess the current relevance of seniority-based rewarding systems and their ability to adequately reflect employees' performance potential. This is essential to appropriately address the growing concerns about the aging population, sluggish productivity growth, rising labor costs, increased international competition, and emerging forms of labor market flexibilization for the forthcoming decades.

The remainder of this article is organized as follows. Section 2 discusses the theoretical predictions and previous literature on the tenure-performance relationship. Section 3 presents our empirical model and estimation strategy. Section 4 covers institutional details pertaining to Belgium and sets the country in an international perspective. Section 5 presents the data and main descriptive statistics. Section 6 presents and discusses the econometric results. Section 7 concludes the work.

2. Theoretical framework and empirical literature

2.1 Theoretical framework and hypotheses

The human capital theory (Becker, 1964) identifies a positive contribution of long-tenured employees to organizational performance. This is underpinned by notions of firm-specific human capital (Becker, 1964) and tacit knowledge (Polanyi, 1966;1958). Over the course of their employment, workers acquire firm-specific expertise, by means of investments in training and on-the-job learning. Accordingly, tenure reflects high levels of accumulated human capital and a large productivity potential. At the same time, long-tenured careers are also associated with extensive (organization-specific) tacit knowledge. Dosi and Grazzi (2010, pp. 176) referred to tacitness as 'the inability by the actor(s) implicated, or even by sophisticated observers, to explicitly articulate the sequences of procedures by which 'things are done', problems are solved, behavioural patterns are formed, etc'. Tacit knowledge has a personal quality, which cannot easily or schematically be transferred. Consequently, it does not remain in an organization after a worker's departure (Grant, 1996; Nonaka, 1994; Polanyi, 1966). This implies that internalizing an organization's values, norms, procedures, principles and social networks (van de Brake et al., 2019) is expected to bolster the tenured workers' potential and, as a result, positively affect the core task performance (Steffens et al., 2014). Such predictions are particularly valid in workplaces that rely heavily on firm-specific knowledge and 'corporate memory' (e.g., more specialized goods and services), and where long firm-specific experience is a guarantee of a well-performed process (Bryson et al., 2020).

Other theoretical frameworks endorse such predictions. The attraction-selection-attrition (ASA) model (Schneider, 1987) emphasizes that long-tenured workers are more likely to exhibit elevated performance, as they embody both high person-organization (P-O) fit and extensive organizational knowledge (Steffens et al., 2014; Ng and Feldman, 2010). This self-selection of better employees is the result of three, closely intertwined processes. People are differentially attracted to organizations on the basis of a given fit between personal and organizational characteristics (i.e., attraction). In turn, firms are more likely to hire and retain those employees whose profile matches the organizational environment (i.e., selection). Finally, employees self-select out of jobs perceived as having a low fit with their values and attributes (i.e., attrition). Over time, such a cycle is expected to lead to higher organizational homogeneity and, accordingly, a higher retention, satisfaction and commitment of the employees (Schneider et al., 1995; Schneider, 1987; Bretz et al., 1989). The organizational embeddedness theory (Ng and Feldman, 2010; 2007; Mitchell et al., 2001) offers a similar perspective. Long-tenured workers are assumed to become highly 'embedded' and, in turn, exhibit a higher motivation to perform (Willim Lee et al., 2014;

Sun et al., 2012). Higher 'embeddedness' results from more extensive social links having been developed within the organization, a better match (or fit) between the organizational requirements and employee's abilities/interests, and higher sunk costs (e.g., material or psychological benefits that would be lost by leaving the organization).

Nevertheless, the above arguments appear to be partly offset by another growing strand of literature that supports a curvilinear (i.e., inverted U-shaped) relationship between tenure and performance. This implies that, from a certain point onward, marginal increases in tenure might become progressively less beneficial for a firm's performance (Sturman, 2003). Various mechanisms might be at play. Extending the predictions of the human capital theory, it may be argued that the bulk of acquirable organization-specific knowledge (and its underlying performance potential) is bound to reach a natural cap, as one's tenure gradually progresses (Shaw and Lazear, 2008). This is consistent with the existence of learning curves. In turn, the beneficial impact of additional tenure is expected to be relatively larger at lower levels of overall experience than when sufficiently long years of service have been attained (Steffens et al., 2014; Ng and Feldman, 2010; Sturman, 2003).

Relatedly, as tenure increases, an individual necessarily grows older. In turn, aging may adversely affect performance, as a result of a decline in physical and cognitive abilities (Picchio, 2015).[2] In addition, although skill obsolescence may materialize at any age (depending on the changing market demands), older workers may be particularly affected by this phenomenon (De Grip, 2006). This is likely to have significant repercussions on workplace performance, particularly when new procedures, technologies and changes in organizational skills are introduced (Bryson et al., 2020; Allen and De Grip, 2012; van Loo et al, 2001).

Moreover, performance might be hampered by the degree of 'continuance commitment' linked to organizational tenure (Uppal, 2017; Allen and Meyer, 1990). Continuance commitment reflects the perceived costs associated with leaving one's organization (Meyer et al., 2002). Such an argument is pertinent to tenure, which acts as a proxy for accumulated sunk costs (Cohen, 1993; Becker, 1960). Indeed, when joining an organization, workers generally invest time and effort in accumulating organization-specific knowledge. The longer the tenure is, the more significant the nature and/or magnitude of the investments and efforts that would be lost by leaving such an organization.

[2] Cognitive abilities are generally distinguished into 'fluid' and 'crystallized' intelligence (Horn and Cattel, 1967; 1966). Fluid intelligence reflects the ability to solve problems in novel situations, independently of the acquired knowledge. This is associated, inter alia, with problem solving, abstract reasoning, attentional capacity, learning/processing speed, and adaptability to new work situations. Crystallized intelligence refers to the ability to use knowledge acquired previously through education and experience (Cattel, 1963). Although fluid cognitive abilities, together with dexterity and physical strength, appear to deteriorate with age, the opposite occurs for crystallized abilities (such as verbal abilities and tacit knowledge) (Bussolo et al., 2015; Picchio, 2015; Desjardins and Warnke, 2012; Giniger et al., 1983). See also Bryson et al (2020) for recent empirical evidence on the impact of age on workplace performance.

Some employees might even perceive their long organizational tenure as a 'barrier' to their search for alternative employment opportunities, given the higher mismatch between their accumulated firm-specific human capital and that conceivably desired by other employers (Hirsch et al., 2000). This is all likely to be exacerbated by the presence of seniority-based entitlements (Eurofund, 2019; Lazear, 1980, 1971). As a result, employees may end up feeling the need to stay longer in a firm to avoid incurring such costs and may then decide to do the very minimum required to retain their employment (Meyer et al., 1989).

From this discussion, we draw up the first hypothesis as follows:

Hypothesis 1: The impact of tenure on productivity is curvilinear (i.e., inverted U-shaped). After attaining an optimal level, tenure becomes progressively less beneficial to firm productivity.

Several mechanisms may be expected to affect the tenure-productivity relationship. Workforce characteristics, such as the nature of a given task and job, may be particularly relevant. Indeed, tenure (through accumulated firm-specific human capital) may exert a greater positive influence on performance in settings characterized by a certain degree of repetitiveness. Routine tasks, which typically feature 'diminishing return' learning curves, are relatively quick and easy to learn, thereby requiring workers to generally spend less time in 'transition-like' stages (Murphy, 1989). In this case, one's learning progresses quite rapidly at the beginning, but plateaus equally swiftly, once full proficiency is reached.[3] Hence, when tasks are sufficiently routine, extensive firm-specific tenure allows workers to perform adequately and with little effort, and this leads to straightforward performance gains. However, from a given point onward, diminishing marginal returns to tenure might occur. This outcome may coincide with a variety of settings. Firstly, in line with our previous discussion, long-tenured employees are likely to reach a certain cap on learning since, by definition, a more routine task progressively moves workers toward the high-end of the learning curve, where no other valuable firm-specific knowledge can be acquired. Thus, marginal increases in tenure may exert a less beneficial impact on performance once the workers have attained high levels of overall workplace experience. Secondly, the decreasing nature of the impact may suggest performance-disruptive feelings – such as boredom, loss of motivation and lower engagement – that arise from the low intellectual stimulation associated with task repetitiveness over time. In addition, both effects may be further exacerbated by the development of 'continuance commitment' and, more

[3] In this regard, it is important to stress that the steepness/length of the learning curve might vary, even within tasks characterized by a certain degree of repetitiveness. This may be the case, for instance, of relatively routine tasks performed in highly-complex occupations (e.g., a professional performing a given task, sufficiently routine in nature, but which nonetheless requires far more time and effort for the worker to become fully proficient at).

relevantly, by age (i.e., *via* a decline in cognitive and physical abilities). Indeed, firm performance may be unfavorably affected by the presence of tenured (and older) workers in more routine settings, for instance, when a firm's production processes either require physically fit employees or are adapted through the introduction of more recent technologies (i.e., requiring up-to-date skills; Bryson et al., 2020).

As for non-routine tasks, which imply higher variety, novelty and flexibility, tenure is not expected to necessarily exert an impact on performance. On the contrary, firm-specific experience may only play a rather marginal role (if any). Intuitively, in more unpredictable and ever-changing contexts, cognitive and manual abilities are much more likely to dominate the potential benefits of long tenure (e.g., greater familiarity with internal procedures, past organizational knowledge) to ensure an effective performance.

An analogous discussion is that related to the level of job complexity. Low-complex jobs, such as assembly line or clerical work, are mostly characterized by shorter learning curves. In this case, an extensive tenure (as a synonym of a well-learned process) is expected to have remarkably beneficial impacts on performance (Sturman, 2003; McDaniel et al., 1988). However, because of the lower complexity, decreasing returns to tenure are also more likely to occur in the long term, as the extent of the (positive) impact of additional firm-specific experience is expected to be lower for higher tenure levels (Sturman, 2003). Similar predictions of decreasing returns hold when considering the other intuitions (i.e., performance-disruptive feelings, age, continuance commitment) provided under the setting of routine tasks. An opposite argument applies to highly-complex jobs (e.g., that of professionals). Given their greater intricacy, such jobs tend to exhibit 'increasing return' learning curves. This implies that workers rely on their cognitive abilities for a longer period. Hence, the rate of performance progression may be slower at the beginning, then rise over time, until the job is fully mastered. In this case, it is possible to expect a delayed (and, potentially, more enduring) positive impact of tenure on performance, as the benefits of accumulated experience materialize after some time, but also tend to last longer (Sturman, 2003). However, cognitive abilities are likely to play a far more critical role in highly-complex jobs. It is thus possible to expect increasing returns to tenure for such jobs to be at least partially attenuated by age-driven declines in cognitive abilities.

Such arguments can also be extended to include firm characteristics as salient moderators. Tenure is expected to have a greater (and positive) influence on performance in environments that feature simpler production processes, such as industrial and low-knowledge intensive firms, where learning curves are somewhat easy to climb. These contexts also generally coincide with lower job complexity and higher average task routineness. On the other hand, complex environments typically operate on markets that are 'highly fluid, rapidly changing and characterized by a high degree of uncertainty, resulting from ambiguity with regard to performance, quality and appropriateness' (Strambach, 2008; pp. 155). Innovation- and ICT-intensive workplaces are generally found to exhibit a positive correlation with higher employment in highly-complex skills and non-routine tasks, which in general require problem-solving and decision-making activities (Marcolin et al., 2016c). In such contexts, being particularly tenured might not matter so much, since the knowledge or expertise requirements for a specific (technical) discipline may rather be met by less tenured, younger, more up-to-date, innovative and fresh-thinking employees. Consistently with our theoretical predictions on non-routine tasks and highly-complex jobs, we can therefore expect cognitive abilities to be particularly relevant for an effective performance in complex production environments, thus relegating firm-specific experience to a more marginal role.

In view of the previous discussion, we formulate our second and third hypotheses as follows:

Hypothesis 2: Workforce characteristics moderate the tenure-productivity relationship. Tenure is more likely to matter for performance in contexts with a certain degree of task routineness and lower job complexity, but not for non-routine tasks. A delayed (and potentially enduring) beneficial impact of tenure is expected in highly-complex job environments.

Hypothesis 3: Firm characteristics moderate the tenure-productivity relationship. Tenure is more likely to matter for performance in firms with highly routinized and less complex production processes. Factors such as industry, the type of technology, and the degree of knowledge- and capital-intensity may affect the relationship accordingly.

2.2 Previous empirical studies

Several studies have explored the tenure-performance nexus. Some of them found no impact (Flabbi and Ichino, 2001; Medoff and Abraham, 1981; 1980) or a positive impact of tenure on productivity (Auer et al., 2005; Blakemore and Hoffman, 1989), whereas some successive works (Uppal et al., 2017; Steffens et al., 2014; Ng and Feldman, 2010; Auer et al., 2005; Sturman, 2003) pointed to tenure as a vector of diminishing beneficial returns on performance. However, these studies differ widely with respect to the type of performance measure used, their data and methods.

Although some of them (Auer et al., 2005; Kramarz and Roux, 1999; Blakemore and Hoffman, 1989) adopt objective performance indicators (e.g., output-based measures), most rely on subjective evaluations (e.g., supervisors' evaluations), which are likely to suffer from well-known biases (Fehrenbacher et al. 2018; Sturman, 2003; Bommer et al., 1995). A robust investigation of the impact of tenure on performance also requires adequate data structures. To this aim, it is crucial to have matched employer-employee data available to construct detailed firm-level measures of the workers' tenure and productivity and to control for both worker- and firm-level characteristics (Card et al., 2014; Abowd and Kramarz, 1998). However, most of the existing studies are based on meta-analyses (Ng and Feldman, 2010; Sturman, 2003), field studies (Uppal et al., 2017), data at the country- (Auer et al., 2005), industry- (Blakemore and Hoffman, 1989), or single-firm-level (Steffens et al., 2014; Flabbi and Ichino, 2001; Medoff and Abraham, 1981; 1980) and therefore only provide either aggregate evidence or lack generalizability.

Moreover, the existing empirical evidence does not generally deal with endogeneity issues stemming from unobserved heterogeneity between firms and simultaneity problems, which are crucial to obtain robust estimates. A notable exception is the work of Kramarz and Roux (1999), who are the only ones to have relied on matched employer-employee panel data while focusing on firm productivity as an objective measure of firm performance and accounting for endogeneity through instrumental variables estimation. Using matched data on French private-sector employees over the 1976-1995 years, they found that employing workers with intermediate levels of tenure has the most beneficial impact on firm productivity.

However, as far as endogeneity issues are concerned, in recent years, structural econometric approaches, based on control-function estimators (CFEs), have been developed to consistently estimate firm-level production functions (Ackerberg et al., 2015), which can easily be augmented with any variable of interest, such as tenure, as in our case. The advantage of CFEs is that endogeneity problems stemming from unobserved productivity levels can be solved by proxying the latter as a function of the observables, called 'control function'. These methods have been used in several recent studies to assess the impact of different factors on productivity, such as sickness absenteeism (Grinza and Rycx, 2020), workers' flows and reallocation dynamics (Grinza, 2020), part-time work (Devicienti et al., 2018), training (Konings and Vanormelingen, 2015), learning-by-hiring effects (Parrotta and Pozzoli, 2012), spillover effects through worker mobility (Serafinelli, 2019), and workforce diversity in terms of age and gender (Vandenberghe, 2013). However, we have found no work in which empirical evidence is used to examine the impact of tenure on productivity within such a robust estimation framework.

We add to this limited empirical literature in four distinct ways. First, we obtain an estimate of the impact of tenure on an objective measure of firm performance (i.e., firm productivity). Second, we go beyond the average (linear) impacts by testing the existence of curvilinear (i.e., inverted-U-shaped) impacts, and complementing this estimation with an investigation on the tenure composition of the workforce (i.e., workers' tenure shares). To do so, we examine how changes in the proportions of low- (up to 5 years), medium- (between 6 and 11 years), and high-tenured (12 years or more) workers affect productivity. In so doing, we account for differentiated impacts over the tenure distribution and heterogeneous patterns on the labor market. Third, we explore heterogeneous effects across relevant workforce dimensions that have not yet been investigated, including the degree of task routineness, the level of job complexity, as well as different types of production environments. This is essential to draw up policy implications on the current relevance of the seniority-performance nexus in the employment relationship. Finally, to the best of our knowledge, we are the first to investigate the impact of tenure on productivity while employing state-of-the-art econometric methods to deal with potential endogeneity issues and relying on rich representative matched employer-employee panel data.

3. Empirical strategy and model identification

To examine the effect of tenure on productivity, we rely on the following log-linear value-added Cobb-Douglas production function:

$$y_{it} = \alpha + \beta_l l_{it} + \beta_k k_{it} + \theta ten_{it} + \tau ten_{it}^2 + \gamma X_{it} + \delta C_{it} + u_{it} \quad (1)$$

The terms y_{it}, l_{it}, k_{it} stand for the (natural logarithms of) value added, labor and capital usage of a given firm i at time t, respectively. The variable ten_{it} measures the average level of tenure in firm i at time t, while ten_{it}^2 represents its squared term. The term X_{it} is a vector of any additional variables of the production process related to the composition of the workforce. It includes the average workers' ages and the shares of older[4], female, medium and highly educated, white-collar, native, part-time, and temporary workers. We also insert a series of other control variables, C_{it}, including dummies for firm-level collective agreement and fixed effects for year, size, region, industry, year-size, and year-industry.[5] Finally, u_{it} represents the error term of the regressions, that is, the production level of firm i at time t that remains unexplained. The latter can be decomposed into two terms: $u_{it} = \omega_{it} + \varepsilon_{it}$. The first term, ω_{it}, is the firm's productivity level at time t that is not observed by the econometrician, but that is partly anticipated at $t-1$ (and then observed

[4] In line with our theoretical predictions, we thoroughly account for the role of age in the tenure-productivity relationship. This is done by controlling for the average age of the workforce as well as for the specific impact of an increase in the proportion of older workers.
[5] Because of their time-invariant nature, the dummies for firm-level collective agreement, and for region and industry are excluded in the specifications that account for firm fixed effects.

at t) by the firm. The second term, ε_{it}, is an idiosyncratic error term, assumed to be uncorrelated with the regressors.

This empirical setting is commonly referred to as the 'augmented production function'. Its intuition is that the firm's production output is not only influenced by standard inputs, such as the amounts of labor and capital, but also by other production factors, which may include the most diverse variables (e.g., workforce composition). Our coefficients of interest, θ and τ, capture the impact of tenure on the firms' overall productive performance (i.e., the tenure's marginal contribution to production output). As our first aim is to assess the impact of tenure on firm productivity, a consistent estimation of θ and τ is crucial.

To this aim, the empirical analysis needs to address several endogeneity concerns, mainly stemming from the possibility of both inputs and tenure responding to the firm's productivity level, ω_{it}, which the firm observes and partly predicts, whereas the econometrician does not. The first issue may arise from the 'simultaneity of inputs' (Marschak and Andrews, 1944). Inputs may be endogenous because they respond to the firm's productivity level. Highly productive firms may be willing to produce more, and thus employ more inputs. Likewise, productivity enhancements (e.g., thanks to the introduction of new process technologies) may raise the usage of inputs. This might lead to the inputs being correlated with ω_{it}.

The second issue, which is specifically related to our research question, is that tenure might also be endogenous.

First, this might be related to an omitted variable bias. Specific firm characteristics, unobserved by the econometrician, may influence both productivity and tenure. On the one hand, a good management and well-designed HR practices may affect the employees' engagement and commitment to the organization, thereby influencing workers' productivity (Vance, 2006). Indeed, good managers may implement effective retention strategies (e.g., providing timely and constructive feedback, building trust, valuing and appreciating employees' input and output). Similarly, functional HR practices may improve a work environment and, consequently, increase the workers' willingness to stay with the organization, as a result of a better work-life balance and increased employee satisfaction (e.g., flexible schedules, healthcare and pension benefits, fair and transparent employee compensation, training and development, coaching, mentoring). On the other hand, the presence of high-quality managers may contribute to higher productivity levels, due to factors that are not necessarily linked to the employees' tenure levels. This results in a correlation between tenure and ω_{it}. Additional unobserved firm characteristics, such as the degree of competition that the firm faces, or its involvement on foreign markets, may also result in a similar bias.

Second, potential problems of reverse causality may arise if tenure affects productivity and, at the same time, is influenced by it. This may happen during periods of economic downturns (booms) or negative (positive) productivity shocks, which induce firms to adjust their workforce and lay-off (hire) workers, thereby affecting the overall level of tenure in the firm. Indeed, tenure is typically found to move counter-cyclically with fluctuations in the business cycle, that is, decreasing during booms and increasing in times of economic upturn (Eurofund, 2015; Abraham and Medoff, 1984; Jovanovic, 1979). Relatedly, certain institutional characteristics, such as EPL, may interact with the business cycle and stabilize employment (and tenure) during economic downturns, although they may also discourage new hires during upswings (Boeri, 1999). Again, this may be expected to create a correlation between tenure and ω_{it}.

As a result of these endogeneity concerns, an OLS estimation of Equation (1) cannot consistently estimate θ and τ (or the other production function parameters, β_l, β_k γ, and δ). It is in fact necessary to adopt an estimation strategy that accounts for the fact that the unobserved productivity level of a firm may fluctuate over time, and that the production inputs and tenure may respond to these fluctuations. The control function approach proposed by Ackerberg et al. (2015) (ACF, from now on), which refined the methods developed by Olley and Pakes (1996) (OP) and Levinsohn and Petrin (2003) (LP), represents a valid solution to endogeneity. The production function in these models can be adapted to any variable of interest, such as tenure, as in our case. In practice, ACF uses the firm's demand for intermediate inputs to proxy for the unobserved productivity level, ω_{it}. The rationale behind this is that intermediate inputs are able to capture the firm's unobserved productivity level. This is because firms can relatively easily adjust their use of intermediate inputs, in response to productivity shocks.

Like the OP and LP methods, the ACF procedure assumes that unobserved productivity follows a first-order Markov process and is homogenous across firms. However, substantial and persistent differences in productivity levels, consistent with the firm-specific fixed components of firm productivity, have been found ubiquitously in data (Syverson, 2011). Not explicitly accounting for them could significantly hinder the ability of the control function estimator to solve the simultaneity bias (Lee et al., 2019). Lee et al. (2019) have recently proposed a way to extend the control function estimators, including the ACF approach, to explicitly account for firm fixed effects, in order to allow firm-specific persistence in productivity levels to be taken into account. Such a methodological extension offers two main advantages. Firstly, it removes any unobserved fixed firm heterogeneity. Secondly, it enhances the ability of the proxy variable to capture and control for the (fluctuations in the) unobserved productivity level.

In our empirical analysis, we perform several estimations of Equation (1), including OLS, ACF, and ACF-FE.[6] In view of the above discussion, we select the ACF-FE as our preferred method. We verify the curvilinear (i.e., inverted-U-shaped) relationship between tenure and productivity throughout our empirical analysis *via* alternative specifications of Equation (1). In the first case, Equation (1) is adapted to estimate the impact on productivity of the tenure composition of the workforce, through changes in workers' tenure shares (i.e., share of workers with low-, medium and high-tenure). Furthermore, when embarking on our moderating analyses, Equation (1) is adapted to examine the impact of additional years of tenure in firms with low and high overall average tenure levels, respectively. In both cases, the same set of control variables as in Equation (1) is used. Appendix A provides a detailed description of our empirical framework and illustrates both the ACF and the ACF-FE estimation methods in detail.

4. The Belgian case in an international perspective

Tenure varies significantly across countries. At the OECD level, the average values range from a minimum of 6.7 years (Lithuania) to maximums of 11.2 years (Portugal) and 12.2 years (Italy). A shorter tenure is more frequent in Baltic countries, Eastern Europe and in some Nordic countries, whereas a longer tenure appears in Southern European countries, Belgium, France, and Germany.[7] Apart from macroeconomic trends, differences in institutional designs have also been identified as contributing factors to heterogeneous levels of tenure (McGowan et al., 2020; OECD, 2019a; 2017).

A stringent EPL, such as high dismissal costs, may stabilize employment during economic downturns, but may also discourage new hires during upswings. More generally, stricter EPL rules may shield workers from management discretion, while increasing employers' cautiousness and selectivity in hiring.[8] This is expected to positively affect the overall tenure of the workforce (Berglund and Furåker, 2016; Auer and Cazes, 2003, Bertola et al., 2000). Highly unionized workplaces also feature significantly longer tenure, due to the unions' involvement in ensuring job security and better working conditions which, in turn, may entail a low voluntary turnover (Molloy et al., 2020; Berglund and Furåker, 2016; Freeman, 1980). A high tenure can generally be found in countries with a strict EPL (on regular contracts) as well as with a greater collective bargaining coverage (Berglund and Furåker, 2016).

[6] The acronym 'ACF-FE' refers to the ACF method with the extension proposed by Lee et al. (2019) to explicitly account for firm fixed effects.

[7] These data were retrieved from the OECD Employment and Labor Market Statistics database.

[8] Such issues have been widely discussed in the literature on labor market dualization (e.g., Piton and Rycx, 2019; Emmenegger et al., 2012; Boeri, 1999).

Seniority-based entitlements are also found to be a key (and widespread) determinant of long-term employment relations across countries. Regular increases in pay with seniority, together with other types of seniority-based bonuses (e.g., extra days of leave, end-of-career allowances) are particularly frequent in wage-setting schemes (Eurofund, 2019). In the EU, seniority pay schemes are enshrined in the law in Bulgaria, Slovenia, and Spain. They are also commonly found as part of collective agreements in Belgium, Denmark, Finland, Italy, Spain, Austria, Cyprus, France and, albeit to a lesser extent, in most other Member States. Some companies also appear to reward tenure even in the absence of legally determined seniority-linked pay scales (Eurofund, 2019).

In this context, Belgium may be considered as an illustrative case study. Its labor market is characterized by significant rigidities, with workers moving less between firms and exhibiting long job tenure (McGowan et al., 2020). In 2019, almost 42.7 percent of Belgian workers had been with the same employer for 10 years or more, as opposed to 33.1 percent at the OECD aggregate level. Belgium also exhibits a remarkable union density (50.3 percent in 2018), and an extensive collective bargaining coverage (96 percent in 2017)[9]. In addition, the Belgian labor market juxtaposes below an average protection of standard employment and an above-average protection of temporary jobs and collective dismissals (Fuss, 2009). Seniority-based pay is also a quite widespread practice across Belgian firms, as it constitutes a key element of sectoral-level collective bargaining (CCE, 2020; Eurofund, 2019; Kampelman and Rycx, 2013).[10] In general, a greater incidence of seniority-based pay has been reported for white-collar workers and in non-commercial sectors. White-collar workers also benefit from a broader definition of seniority to determine their pay progression over pre-determined pay scales, whereas a stricter definition (i.e., years of service with the same employer) is applied to blue-collar workers (CCE, 2020; Vandekerckhove et al., 2018). Most sectoral collective agreements also foresee caps on seniority-based pay after a certain number of years within the same company (CCE, 2020; SPF ETCS, 2018). Nevertheless, wages in Belgium show an increasing trend over time, especially for white-collar workers (SPF ETCS, 2018; Baeten et al., 2018; CCE, 2017; 2014).

Overall, such trends may be indicative of retention strategies undertaken within firms to enhance the employee's productivity potential *via* firm-specific human capital accumulation (CCE, 2020). The existence of steep seniority-wage profiles may encourage firms to invest in their workers' training over time, thus inducing workers to remain with their employer in the long term

[9] The union density and collective bargaining coverage figures were retrieved from the OECD Employment and Labor Market Statistics database.

[10] In Belgium, wage determination is based on contracts (*conventions collectives de travail – CCT*) between employers (or employer associations) and trade unions. Firms, when setting their wage policy, need to take into account all the specificities of the CCTs agreed upon at the national-, sectoral- and firm-levels. Seniority-based pay scales are usually defined at the sectoral level. For a detailed description, see Kampelman and Rycx (2013).

(Storm and Naastepad, 2007; Auer et al., 2005). Promoting loyalty in long-term employees may also foster knowledge spillovers between less- and more-tenured employees (De Meulenaere et al., 2016). Nevertheless, the wages may not necessarily reflect productivity increases, as factors other than human capital (e.g., incentive mechanisms) might interfere with the wage-setting policies (Flabbi and Ichino, 2001; Medoff and Abraham, 1981; 1980). The latter argument is also in line with recent evidence of a sluggish annual productivity growth (counterbalanced by increasing labor costs) that has characterized the Belgian economy over the past decade (OECD, 2019b; Baeten et al., 2018).

To this aim, Baeten et al., (2018) highlight the existence of a 'golden-cage effect'. The idea is that a boundless link between remuneration and seniority may create a disincentive for employees to leave the organization, with significant repercussions on performance. Seniority-based pay generally acts as a long-term incentive to stay with the current employer.

However, over time, this 'golden cage' is more likely to retain low performers. Indeed, high-performing employees can easily find better opportunities (rewarding skills and performance over mere tenure) outside their organization. This discussion highlights that the potential of tenure affecting productivity might depend to a great extent on the underlying institutional setting. In this regard, the Belgian case exemplifies structures that prevail across several advanced economies, and thus lays the groundwork for important policy insights.

5. Data and measurement

Our empirical analysis relies on a combination of two large-scale data sources, covering the 2005–2016 period. The first data set, provided by Statistics Belgium, is the Structure of Earnings Survey (SES). This is a matched employer-employee data set of a sample of firms that operate in Belgium, employing at least 10 workers and belonging to sectors within sections B to N of the NACE Rev.2 classification of economic activities.[11] The SES data set contains a wealth of information, provided by the human resources departments of the firms, on the characteristics of the company (e.g., economic activity sector, number of workers, level of collective wage bargaining) and its workers (e.g., gender, age, education, tenure, occupation). This data set is particularly relevant for our purposes, as it provides information on the number of years each worker has been with the same employer.[12]

[11] The SES thus covers the following sectors: mining and quarrying (B); manufacturing (C); the supply of electricity, gas, steam and air conditioning (D); water supply, sewerage, waste management and remediation activities (E); construction (F); wholesale and retail trade; motor vehicle and motorcycle repairs (G); accommodation and food service activities (I); transportation and storage (H); information and communication (J); financial and insurance activities (K); real-estate activities (L); professional, scientific and technical activities (M); administrative and support service activities (N).

[12] The SES data set is the result of a complex stratified sampling design. The stratification criteria refer to the region (NUTS-groups), the economic activity sector (NACE-groups), and firm size. The sample size in each stratum depends on the firm size. The sampling

However. the SES data set does not provide any financial information on firms. To obtain this source of information, which is necessary to estimate our augmented production function, the SES is matched with a different firm-level data set, the Structure of Business Survey (SBS). The latter is also conducted by Statistics Belgium, and provides information on several financial variables, including value added, the value of investments in tangible fixed assets, and expenditure on intermediate inputs.[13] Statistics Belgium has carried out the matching between the SES and the SBS data set using each firm's social security number as a firm identifier. We refer to this matched employer-employee data set as 'SES-SBS'.

We complement our data with information on workers' tasks, identified as the routine content of occupations. To do so, we follow Marcolin et al. (2016a; 2016b) and draw on information from the OECD Programme for the International Assessment of Adult Competencies (PIAAC) survey for Belgium. This data source allows to obtain a precise, country-specific identification of the routine intensity of occupations, directly relying on answers provided by workers (in each OECD country) to questions about their daily work.[14] In particular, we extract data on four PIAAC questions. The latter measure, on the one hand, the routine content of occupations *via* an assessment of the workers' degrees of freedom in task sequentiability and task flexibility and, on the other hand, the frequency with which workers plan their own activities and organize their own time.[15] The four questions are used to construct an index of routine intensity of tasks.[16] Median values of the index (at the 2-digit ISCO08) are then used to rank the occupational categories into four quartiles (i.e., high-routine, medium-routine, low-routine, non-routine).[17] Finally, the four

percentages of the firms are equal to 10, 50, and 100 percent when the number of workers is lower than 50, between 50 and 99, and above 100, respectively. The sampling percentages of employees within the firm also depend on the firm size. The sampling percentages of employees reach 100, 50, 25, 14.3, and 10 percent when the number of workers is lower than 20, between 20 and 50, between 50 and 99, between 100 and 199, and between 200 and 299, respectively. Firms that employ 300 workers or more have to report information on a specific number of employees. This number ranges between 30 (for firms with between 300 and 349 workers) and 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).

[13] The SBS data set does not cover the whole financial sector (NACE K) as SES does, but only two of its subsectors: 'Other Financial Intermediation (NACE 649) and 'Activities Auxiliary to Financial Intermediation' (NACE 66).

[14] As argued in Marcolin et al. (2016a), the commonly used measures of routine content of occupations (such as those relying on the US-based O*NET database) may instead be somewhat more limited, especially when applied to other countries. The reason is twofold. First, the related task routineness measures are often chosen *ad-hoc* (e.g., experts assigning scores to different indicators characterizing the occupations). Second, they often rely on the assumption that the routine content of tasks is time-invariant and that it does not vary across countries. Therefore, using country-specific PIAAC survey information allows to overcome such limitations.

[15] The four questions that we retrieved from the PIAAC database are the following: *d_q11a* (Sequentiability – 'To what extent can you choose or change the sequence of your tasks?'); *d_q11b* (Flexibility – 'To what extent can you choose or change how you do your work'); *f_q03a* (Frequency of ones' own activities – 'How often your current job involves planning your own activities?'); *f_q03c* (Frequency of ones' own time – 'How often your current job involves organising your own time?'). The answers to each question are assigned a score with a minimum of 1 (e.g., 'Never') to a maximum of 5 (e.g., 'Every day').

[16] In line with Marcolin et al. (2016a, 2016b), OECD (2008) and Nicoletti et al. (1999), the set of weights used for the construction of the routine intensity index involves the use of the principal component analysis. As in Marcolin et al. (2016a, 2016b), we assume that the four weights should sum up to one. Consequently, our routine intensity index ranges between 1 (most routine-intensive task) and 5 (least routine-intensive task). Individuals with missing information on at least one of the answers to the questions have been discarded.

[17] For instance, we find 'Chief Executives, Senior Officials, and Legislators' (ISCO 11); in occupations categorized as 'non-routine-intensive' we find 'Business and Administration Associate Professionals' (ISCO 33) in 'low-routine-intensive' occupations; we find 'Numerical and Material Recording Clerks' (ISCO 43) in the 'medium-routine-intensive' category; finally, we find 'Stationary Plant and Machine Operators' (ISCO 81) in the 'high-routine-intensive' occupations.

quartiles are merged, at the occupational level (i.e., 2-digit ISCO08), with the matched 'SES-SBS' data set.[18]

In the empirical analysis, we measure the output with the (deflated) value added. We measure labor considering the total number of employees (expressed as full-time equivalent employees – FTE). We compute the capital from the flows of (deflated) value of investments in tangible fixed assets, by applying a version of the perpetual inventory method, as described in OECD (2009, pp. 221). The latter method is based on the idea that capital results from investment flows after correction for retirement and efficiency loss. In line with the standard practice, we assume a 5 percent annual depreciation rate of capital. Finally, we measure the intermediate inputs, as used in the ACF and ACF-FE procedures, to proxy for the firm's unobserved productivity level, with the (deflated) expenditure on raw materials, consumables, commodities, services, and other ancillary costs.

Our empirical analysis focuses on single-plant firms with at least 3 years of consecutive observations. The focus on single-plant firms is necessary to ensure that the financial information provided by the SBS is at the same level as the workforce-related information provided by the SES. The rationale behind the 3 year threshold lies in the specific features of the ACF and ACF-FE techniques. Firstly, at least 2 years of consecutive observations are needed to perform these techniques. Secondly, as they are highly demanding, in terms of data quality (e.g., the ACF-FE only exploits within-firm information and executes complex nonlinear estimations), and an additional year of consecutive observations is thus required to obtain more reliable and precise estimates. Our data set mainly collects medium and large firms, as the sampling percentages of the firms in the SES data set increase with firm size (see footnote 12). Finally, we do not consider a few firms for which public financial control exceeds 50 percent[19], or providing valid information on fewer than 10 employees. Our final data set therefore focuses on single-planted, generally medium- and large-sized firms operating in the private sector in Belgium, with the exception of a large part of the financial sector (NACE K). Our final sample represents the firm-level collapsed version of the cleaned matched employer-employee data set, and it consists of an unbalanced panel of 6,971 observations for 1,646 firms over the 2005-2016 years.

Table 1 reports some descriptive statistics (at the firm level) of our sample. On average, the firms in our sample employ about 200 workers and produce a value added of around 18 million euros per year. Women represent about 26.6 percent of the workforce in the average firm, about 49 percent of the workers are in their prime age, and the vast majority of them (74 percent) do not

[18] This involved only a minor loss of observations (less than 2 percent) of the original SES-SBS data set.
[19] The rationale is derived from the standard productivity theory and its requirement that prices must be economically meaningful.

hold tertiary education qualifications. Over half (55 percent) of our employee-level sample is made up of blue-collar workers; 89 percent is represented by workers involved in tasks exhibiting some degree of routineness (i.e., low-, medium- and high-routine tasks), 5.6 percent by part-time workers, and around 3 percent by those with temporary contracts. A few firms belong to the mining and quarrying sector (0.27 percent), more than half to the manufacturing sector (55.2 percent), 10.2 percent to the construction sector, while the rest operate in trade (11.7 percent) and services (34.2). Firms that employ fewer than 50 workers make up 19.8 percent of our sample, 54.9 percent of the firms employ between 50 and 250 workers, while 25.2 percent employ more than 250 workers.

Table 2 shows descriptive statistics on tenure across different firm environments. In our overall matched sample, the mean tenure stands at 9.8 years. This is consistent with the low between-firm worker mobility that characterizes the Belgian labor market. On average, firm environments characterized by lower job complexity and the absence of task routineness exhibit the longest tenure. Employment duration is also found to be longer in industrial, more capital-intensive, non-knowledge-intensive, and ICT-reliant firms.

6. Results

6.1. The overall impact of tenure on productivity

In this section, we show the results obtained from the estimation of Equation (1), aimed at measuring the overall curvilinear impact of tenure on productivity. We report the OLS, ACF, and ACF-FE estimates in Table 3. As discussed in Section 3, our preferred estimation method is ACF-FE. Our estimates control for a large set of workforce (i.e., vector X_{it}) and firm characteristics (i.e., vector C_{it}). The former includes the workers' mean age as well as the share of the firm's workforce by age, gender, education, occupation, country of birth, contract duration (i.e., permanent *versus* fixed-term), and working time arrangement (i.e., part-time *versus* full-time). Our vector of firm characteristics includes dummy indicators for firm-level collective agreement; a set of dummy variables for the firm's size, region and industry; and year, year-size, and year-industry fixed effects. The ACF-FE estimation also removes firm fixed effects. Standard errors are robust to heteroskedasticity and clustered at the firm level. In the ACF and ACF-FE estimations, we compute firm-level cluster-robust bootstrapped standard errors.

Our OLS estimates in Column (1) show that the coefficient associated with mean tenure is positive and significant (0.019), whereas its squared term is negative and significant (-0.0004). This implies that tenure exhibits a curvilinear (i.e., inverted-U-shaped) relationship with respect to productivity. Nevertheless, the OLS estimation is likely to suffer from endogeneity problems, stemming from unobserved characteristics of the firm and reverse causality. On the other hand, the ACF estimation provides more robust estimates since it controls for the fact that inputs and tenure can respond to productivity fluctuations. The ACF estimate (Column 2) of the impact of tenure is again found to be significantly curvilinear. The last columns in Table 3 report the ACF-FE estimates. As discussed earlier, ACF-FE enhances the ability of the control function method to capture the firm's unobserved productivity level, by explicitly removing firm fixed effects. The ACF-FE estimates in Column (3) confirm that, overall, tenure exhibits an inverted-U-shaped relationship with productivity. The coefficient on the linear tenure term is estimated to be 0.014, whereas the estimate for the quadratic tenure term is -0.0003 (both statistically significant at conventional levels). The impact of tenure on productivity is thus positive (albeit with decreasing returns) up to a certain point, after which it becomes negative. This inflection point occurs at around 23 years of average tenure in a firm, thus implying that any additional years of services with the current employer exert a positive (negative) impact on firm productivity before (after) that threshold. Notably, as such an inflection point occurs at substantially high levels of tenure (top 1 percent in the firm-level tenure distribution), marginal increases in average tenure are beneficial for firm productivity for most of the firms. In short, these results appear to uphold *Hypothesis 1*.

In order to complement this finding, we investigate the tenure-productivity nexus on the tenure composition of the workforce. We estimate, *via* ACF-FE, a specification of Equation (1), in which we look at how changes in the proportions of low- (until 5 years), medium- (between 6 and 11 years), and high-tenured (12 years or more) workers affect firm productivity. The share of workers with low tenure is our reference category. Our results in Column (4) of Table 3 show that the coefficient associated with the share of medium-tenured workers is positive and significant (equal to 0.218). The estimated coefficient associated with high-tenured workers is also positive and significant, but lower than the previous case (0.145). This implies that if the fraction of medium-tenured workers increases by one percentage point, productivity increases by around 0.22 percent, whereas an increase in the fraction of high-tenured workers by the same amount leads to a productivity increase of only 0.15 percent. These results thus appear to corroborate the existence of diminishing marginal returns to tenure on productivity. All in all, such findings point to an inverted-U-shaped impact of tenure on productivity, whereby a positive, though decreasing, impact emerges for almost all the firm-level tenure distribution. The existence of decreasing marginal returns to tenure is also confirmed by our analysis on the tenure composition of the workforce.

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

We formulate two additional hypotheses on how certain workforce and firm characteristics can moderate the tenure-productivity link in Section 2. In this sub-section, we empirically test them *via* a set of moderating analyses. Consistently with the previous findings, we continue to focus on the curvilinear trend of the relationship. To do so, we rely on a specification of Equation (1), in which we interact the firm-level mean tenure variable with dummies that indicate whether the firm has low or high levels of tenure, respectively. The associated coefficients thus serve as indicators of the impact of additional years of tenure in contexts with low and high overall tenure. In this regard, we set our threshold at an intermediate value of firm-level tenure (i.e., 12 years), as this corresponds to the point along the tenure distribution at which decreasing marginal returns to tenure start occurring. We then estimate this specification through ACF-FE across a wide range of different firm environments (i.e., we conduct estimations on split samples, constructed on the basis of a wide set of workforce and firm dimensions).

According to *Hypothesis 2*, tenure may exert a strongly positive and significant – although decreasing – impact on productivity in firms characterized by a certain degree of task routineness and lower job complexity, respectively. No impact is expected on those firms that on average perform non-routine tasks. However, a delayed (and potentially enduring) productivity impact of tenure is expected for highly-complex jobs. To test the relevance of tasks, we focus on firms characterized by the absence of routineness as opposed to those exhibiting a certain degree of routineness. In practice, we distinguish such categories on the basis of whether the share of non-routine and routine jobs[20] is above the panel average, respectively. We distinguish between low- and high-skilled contexts to analyze job complexity. In particular, we define those firms that feature a higher share of low-to-medium-skilled occupations than the panel average as 'low-skilled environments'. Similarly, we define those firms that present above-average shares of high-skilled occupations as 'high-skilled environments'.[21]

The results are shown in Table 4. When looking at relatively routine contexts, the estimated coefficients for the interaction of mean tenure with both low and high overall tenure are statistically significant and equal to 0.011 and 0.008, respectively. An additional year of tenure is therefore found to exert a significantly beneficial impact on productivity in situations where tasks are generally characterized by a certain degree of routineness. This is consistent with our theoretical predictions as, in these contexts, seniority with the current employer underpins extensive

[20] Occupations that fall into the low, medium, and high-routine quartiles of our routine intensity index are categorized as 'routine jobs' (see Section 5 for details).

[21] Low-to-medium-skilled occupations (belonging to 'low-skilled environments') include craft and related trade workers, plant and machine operators and assemblers, elementary occupations, clerical support workers, services and sales workers. High-skilled occupations (belonging to 'high-skilled environments') include managers, professionals, technicians and associate professionals.

organizational knowledge on how to perform adequately and with little effort. Relatively routine tasks are in fact characterized by steeper learning curves, which are easier to climb. This is the case, for instance, of product packaging or data entry, or of tasks performed in production processes focused on specialized goods and services (and where firm-specific experience becomes a performance-enhancing asset; Bryson et al., 2020). Nevertheless, as expected, we also find decreasing marginal returns to tenure. Consistently with our theoretical predictions, this may be linked to the workforce experiencing knowledge-related barriers (e.g., the introduction of a new technology, caps on learning) and/or declines in cognitive and physical abilities, an increased sense of boredom, a loss of motivation, lower engagement, and continuance commitment. On the contrary, when looking at prevalently non-routine contexts, the impact of tenure on productivity is not found to be statistically significant, regardless of the overall average tenure in the firm. In line with our hypothesis, and given their implicit unpredictability and irregularity, non-routine tasks prevalently benefit from cognitive and manual abilities, rather than extensive firm-specific experience, to achieve improved performance.

As far as job complexity is concerned, tenure seems to be beneficial to a great extent for firm productivity across the entire skill spectrum. As expected, when looking at low-skilled environments (e.g., those involving assembly-line workers or other jobs that on average require lower skills), the estimated coefficients for firms with low and high overall average tenure are statistically significant and amount to 0.025 and 0.017, respectively. In line with the effect found for routine tasks, these results confirm that, in contexts with lower job complexity (i.e., shorter learning curves), the positive impact of accumulated tenure is stronger, but decreases for higher levels of tenure. On the other hand, a delayed (and enduring) impact of tenure on productivity is found in high-skilled environments (e.g., those involving specialized technicians or professionals). Once again, this is in line with our theoretical predictions. In this case, the coefficients are positive, statistically significant, and with increasing magnitude (0.011 and 0.013 for low and high overall average tenure, respectively). Our results highlight that, in highly-complex jobs, workers usually require a longer time to fully acquire all the necessary competencies/knowledge to become fully performing. Additionally, when comparing the coefficients associated with high levels of tenure for low- and high-skilled environments (i.e., 0.013 *versus* 0.017), we find support to our intuition that cognitive abilities may partly offset the positive effects of productivity accrued through firm-specific experience when the job is more complicated and, potentially, less monotonous.[22] Overall, such results uphold *Hypothesis 2*.

[22] For instance, in our sample, complex occupations such as 'Chief Executives, Senior Officials, and Legislators' (ISCO 11) fall into the 'non-routine-intensive' category (see footnote 17).

According to *Hypothesis 3*, which extends the discussion related to tasks and job complexity, we expect tenure to exert a significant impact on performance in environments that feature highly routinized and less complex production processes and, more generally, where firm-specific experience results in a rapid mastery of a job. To this end, we identify a set of relevant firm characteristics, and categorize firms on the basis of their sector (i.e., industrial *versus* non-industrial), degree of knowledge-intensity (i.e., knowledge-intensive *versus* non-knowledge-intensive), type of technology (ICT *versus* non-ICT), and capital-intensity (i.e., capital-intensive *versus* non-capital-intensive). The results are reported in Table 5.

Our ACF-FE estimates highlight a significant and beneficial impact of tenure – albeit with mostly decreasing marginal returns – on firm productivity in high capital-intensive and industrial firms. This may be illustrative, for instance, of the important role of tenure in contexts that are highly dependent on investments in fixed assets (e.g., automobile manufacturing industry) and which may require employees to support machines through somewhat routine-intensive tasks and jobs of lower complexity (Marcolin et al., 2016c; Acemoglu & Autor, 2011; Goos et al., 2014). A similar rationale applies to what we find for non-knowledge-intensive and non-ICT reliant firm environments (0.025 for low tenure, 0.015 for high tenure; 0.007 for low tenure, 0.005 for high tenure; respectively). All these cases reflect our findings on workforce characteristics, as decreasing marginal returns to tenure have mostly been observed (i.e., lower productivity impacts for high levels of overall average tenure).[23] These instances are, once again, coherent with our predictions of steeper learning curves, given the relatively simpler nature of tasks and processes involved therein.

Interestingly, in knowledge-intensive environments (e.g., scientific research, telecommunications), we detect a significantly negative impact (-0.009) for high levels of average tenure. This is consistent with the findings that innovation- and ICT-intensive industries generally exhibit a positive correlation with employment levels in non-routine occupations and highly-complex occupations. Therefore, our finding is in line with the idea that, in firms characterized by more dynamic, innovative, and fast-paced processes, the knowledge or expertise requirements for a specific (technical) discipline may rather be met by less tenured, younger, more up-to-date, innovative and fresh-thinking employees. This is also in line with the results found for highly-complex firm environments. Cognitive abilities thus appear to dominate the potential benefits of tenure (stemming, for instance, from a greater familiarity with internal procedures) and are essential for increased performance in highly innovative and technological industries. The obtained results on firm characteristics thus uphold *Hypothesis 3*.

[23] An exception is represented by high capital-intensive firms, where the two coefficients retain a similar magnitude.

7. Conclusions

This paper has investigated the impact of firm-specific experience (i.e., tenure) on an objective measure of firm performance (i.e., productivity). To the best of our knowledge, this paper is the first to provide empirical evidence on the tenure-productivity relationship (across a wide range of workforce and firm dimensions) using rich longitudinal matched employer-employee data and robust estimation techniques. We have dealt with the endogeneity issues that arise from unobserved firm heterogeneity and reverse causality by adopting a modified version of recent semiparametric control function approaches (i.e., ACF and ACF-FE).

In line with the recent theoretical predictions, we find that tenure exhibits an inverted-U-shaped relationship with respect to productivity. The impact of tenure on productivity is thus positive (albeit with decreasing returns) up to a certain point, after which it becomes negative. However, the inflection point of our relationship occurs at a high level of average tenure in the firm, thus implying that additional years of service with the current employer exert a positive impact on firm productivity for most of the firms in our sample (more than 99 percent). Our complementary analysis on the tenure composition of the workforce corroborates the existence of decreasing marginal returns to tenure. Consequently, our results show that the tenure-driven benefits achieved from extensively accumulated human capital, tacit knowledge, workers' self-selection, and higher embeddedness within organizations do not appear to endure over time.

We have also found that the impact of tenure differs widely across the workforce and firm characteristics. Tenure is particularly beneficial for productivity in contexts characterized by a certain degree of routineness and lower job complexity. Consistently, our findings indicate that tenure is more relevant for performance in industrial and high capital-intensive firms, as well as in firms that are less reliant on knowledge- and ICT-intensive processes. Such results are in line with predictions of stronger benefits for firm-specific experience in contexts with relatively steep learning curves, which leads workers to become fully performing at what they do in a shorter period of time. Nevertheless, the decreasing nature of the impact may coincide with a sense of boredom\loss of motivation, continuance commitment, or with the fact that a cap on organizational knowledge (and the related performance potential) has been reached. On the other hand, a delayed (and more enduring) impact of tenure on productivity is found in high-skilled environments. This reflects higher job complexity and longer learning curves. In terms of firm characteristics, the type of sector, the type of technology, and the degree of knowledge- and capital-intensity affect the returns to tenure to a great extent over time. The impact of tenure on performance is particularly beneficial in industrial and high capital-intensive contexts, as well as in non-knowledge-intensive and non-ICT-reliant firms. Such findings are consistent with the idea of tenure exerting a direct (and positive) impact on performance when production and learning processes are straightforward in nature.

From a policy perspective, our findings have wide implications. In line with recent debates, the main implication is that tenure is not necessarily a panacea for improved firm productivity. On the contrary, a careful consideration of workforce and sectoral specificities is essential to design effective employee retention strategies that are compatible with long-term competitiveness and growth. If not adequately offset, decreasing marginal returns to tenure may further exacerbate the economic strains on a firm *via* decreased productivity as well as higher labor costs. This is particularly relevant in contexts in which tenure is rewarded through seniority-based pay mechanisms and which, at the same time, are characterized by a strong wage pressure (i.e., large wage differences between less- and more-tenured workers). In this regard, Baeten et al. (2018) emphasize some criticalities concerning the boundless link between tenure and pay. They found that the latter may result in a 'golden-cage effect'. Their idea, which has also been supported by other studies, highlights that extensively rewarding tenure through progressively higher wages might end up being counterproductive, as only low-performing employees would be retained. Indeed, high performers can easily find alternative employment opportunities in which their skills and performance are valued more than mere seniority.

This discussion is topical, in view of recent demographic developments, characterized by widespread population aging, which imply longer tenures as a result of higher participation rates of older workers (Bryson et al., 2020). In the EU, it is expected that the number of older workers will increase substantially (i.e., by 10 percentage points from 2019 to 2070 – European Commission, 2021). Given the close correlation between wage pressure and labor market participation of older workers (Baeten et al., 2018), it will become a key challenge to keep the workforce productive and engaged for a longer time to sustain competitiveness, economic growth, and healthy public finances over the coming decades. Policy makers should proactively cooperate with social partners to promote a debate on the existing wage policy schemes, which rely on seniority-based pay progression, but are generally accompanied by a sluggish productivity growth. This will be key to laying the groundwork for a better alignment with workers' performance potential, the current labor market trends, workers' needs and expectations, and the firms' long-run success strategies.

In this regard, although no one-size-fits-all approach is compatible with the numerous inter-firm occupational, sectoral, and cultural specificities, the implementation of *ad-hoc* hybrid remuneration schemes could be an interesting way forward. Pay progression and career development could be linked to the acquisition of job-related skills (Eurofund, 2019). Baeten et al.

(2018) also suggest a customizable combination of fixed seniority-based pay and variable performance-related remuneration, enriched with additional flexible rewards, to meet the needs of a diverse and changing workforce. Tenure should be rewarded *via* progressively higher pay during the first years of employment (although conditional to the achievement of a minimally acceptable performance level), when experience has a more direct impact on performance (Sturman, 2003). However, after a certain number of years, such a system should be capped to avoid falling into a 'golden-cage trap'. Pay should then be increased in parallel with individual and collective merit-based performance measures (thus reducing episodes of high turnover, poor loyalty, and social loafing). Additional flexible rewards, such as financial assets, learning and development opportunities, well-being, mobility, and flexibility, may further help to improve employees' engagement and satisfaction, and keep them productive for a longer period.

Our findings also provide relevant insights for human resource management discussions, particularly in those contexts in which the tasks, sectors and occupations are more likely to experience long-term deteriorating effects of tenure on productivity. In this regard, more emphasis should be placed on designing adequate remuneration scheme structures and combining them with effective performance evaluation systems. Viable strategies to minimize the risks of continuance commitment, lower engagement and motivation should also move in the direction of a better skill recognition and appreciation, regular attention to the workers' needs, career development by means of training and development, together with coaching, mentoring, and flexibility opportunities. More efforts should be focused on devising transparent, fair, and cohesive work environments. Extensive social consultation processes and well-designed legislative architectures will be imperative to set up the right incentives.

Table 1: Sample summary statistics (firm-level) – Overall variables

Variable	Notes	Mean	Std. Dev.
Firm characteristics			
Employees	Number of employees expressed in FTE	200.25	335.14
Value added	1000 euros, deflated at 2005 prices	18,507.742	41,669.022
Capital	1000 euros, deflated at 2005 prices	62,078.513	381,329.842
Intermediate inputs	1000 euros, deflated at 2005 prices	58,209.956	438,928.090
Gender, age, education, type of task			
Share of females		0.266	0.242
Share of young workers	At most 34 years of age	0.299	0.169
Share of prime-age workers	Between 35 and 49 years of age	0.494	0.151
Share of older workers	Over 50 years of age	0.206	0.146
Share of workers with a low level of education	Less than a high school diploma (ISCED 1 and 2)	0.287	0.294
Share of workers with a medium level of education	High school diploma (ISCED 3 and 4)	0.456	0.295
Share of workers with a high level of education	More than a high school diploma (ISCED 5, 6, and 7)	0.255	0.276
Share of workers in routine tasks		0.894	0.205
Share of workers in non-routine tasks		0.105	0.205
Share of white-collar workers, of which:		0.443	
Share of managers		0.040	0.079
Share of professionals		0.106	0.181
Share of technicians and associate professionals		0.093	0.157
Share of clerks		0.170	0.202
Share of service workers, and shop and market sales workers		0.034	0.139
Share of blue-collar workers, of which:		0.554	
Share of craft and related trade workers		0.231	0.317
Share of plant and machine operators, and assemblers		0.222	0.302
Share of workers involved in elementary occupations		0.101	0.216
Share of workers with fixed-term contracts		0.030	0.079
Share of part-time workers	<30 hours per week	0.056	0.116
Sectors			
Mining and quarrying		0.002	0.052
Manufacturing		0.552	0.497
Construction		0.102	0.303
Trade		0.117	0.322
Services		0.342	0.474
Firm size			
Fewer than 50 employees		0.198	0.398
Between 50 and 250 employees		0.549	0.497
More than 250+ employees		0.252	0.434
Observations			6,971

Notes: ISCED, international standard classification of education.
Source: SES-SBS data set (years 2005-2016).

Table 2: Sample summary statistics (firm-level) — tenure across firm environments

Variable	Mean	Std. Dev.	Observations
Mean tenure of the overall matched sample	9.80	4.95	6,971
Workforce characteristics			
Mean tenure of non-routine environments	10.21	5.24	1,896
Mean tenure of routine environments	9.64	4.82	5,075
Mean tenure of low-skilled environments	9.83	4.95	4,554
Mean tenure of high-skilled environments	9.73	4.95	2,417
Firm characteristics			
Mean tenure in industrial environments	10.81	4.80	4,585
Mean tenure in non-industrial environments	7.84	4.63	2,386
Mean tenure in high capital-intensive environments	9.96	4.76	3,741
Mean tenure in low capital-intensive environments	9.61	5.15	3,230
Mean tenure in knowledge-intensive environments	8.99	5.29	1,398
Mean tenure in non-knowledge-intensive environments	10.00	4.84	5,573
Mean tenure in ICT environments	10.00	5.08	3,124
Mean tenure in non-ICT environments	9.63	4.83	3,847

Notes: Mean tenure is measured as the number of years a worker has been employed in a given firm. Non-routine environments are defined as firms in which the share of non-routine tasks is above the corresponding panel mean; Routine environments are defined as firms in which the share of routine tasks is above the corresponding panel mean. Low-skilled environments are defined as firms in which the share of low-to-medium-skilled workers (i.e., craft and related trade workers, plant and machine operators, and assemblers, elementary occupations, clerical support workers, services and sales workers) is above the corresponding panel mean; High-skilled environments are defined as firms in which the share of high-skilled workers (i.e., managers, professionals, technicians and associate professionals) is above the corresponding panel mean. Industrial environments include firms belonging to the mining and quarrying, manufacturing and construction sectors. Nonindustrial environments include firms in the trade and services sectors. We followed the Knowledge Intensive Activities classification by NACE Rev. 2, based on Eurostat, to define the knowledge (non-knowledge) intensive environments. In the ICT classification, we classified firms as belonging to sectors that use or produce ICT goods and services intensively and those that do not. Such a subdivision is based on the ICT taxonomy developed by O'Mahony and van Ark (2003) and then adapted to the revised NACE Rev.2 classification. We classified low (high) capital-intensive environments as those firms whose panel-average capital-to-labor ratio is below (above) the median.
Source: SES-SBS data set (years 2005-2016).

Table 3: The overall impact of tenure on productivity

Dependent variable: y_{it}	(1)	(2)	(3)	(4)
Variable	OLS	ACF	ACF-FE	ACF-FE
l_{it}	0.903***	0.781***	0.904***	0.900***
	(0.025)	(0.066)	(0.067)	(0.051)
k_{it}	0.127***	0.226***	0.061	0.062
	(0.010)	(0.042)	(0.066)	(0.055)
Mean tenure	0.019**	0.019***	0.014***	-
	(0.009)	(0.004)	(0.005)	
Mean tenure – squared	-0.0004*	-0.0003*	-0.0003**	-
	(0.000)	(0.000)	(0.000)	
Share of medium-tenured workers (between 6 and 11 years)	-	-	-	0.218**
				(0.090)
Share of high-tenured workers (12 years or more)	-	-	-	0.145***
				(0.024)
Mean worker's age	-0.005	0.002	-0.005*	-0.005**
	(0.005)	(0.004)	(0.002)	(0.002)
Share of older workers	0.055	-0.158*	0.063	0.074
	(0.119)	(0.093)	(0.064)	(0.062)
Share of female workers	-0.103*	-0.053	-0.060	-0.056
	(0.057)	(0.050)	(0.045)	(0.045)
Share of workers with medium and high levels of education	0.164***	0.124***	0.005	0.006
	(0.033)	(0.027)	(0.021)	(0.021)
Share of white-collar workers	-0.508***	-0.343***	-0.037	-0.038
	(0.049)	(0.040)	(0.035)	(0.035)
Share of native-born workers	0.005	0.006	-0.079	-0.072
	(0.076)	(0.066)	(0.058)	(0.059)
Share of part-time workers	-0.293**	-0.151	0.283***	0.297***
	(0.112)	(0.099)	(0.071)	(0.071)
Share of workers with fixed-term contracts	-0.220*	-0.112	-0.019	-0.023
	(0.123)	(0.097)	(0.059)	(0.063)
Firm-level collective agreement	0.038*	0.010	-	-
	(0.022)	(0.018)		
Year dummies	Yes	Yes	Yes	Yes
Size dummies	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	-	-
Industry dummies	Yes	Yes	-	-
Year-Size dummies	Yes	Yes	Yes	Yes
Year-Industry dummies	Yes	Yes	Yes	Yes
Firm fixed effects	No	No	Yes	Yes
				Observations: 6,971

Notes: Standard errors, which are reported in parentheses, are robust and clustered at the firm level. We computed firm-level cluster-robust bootstrapped standard errors in the ACF and ACF-FE estimations. ***, **, and * denote the 1 percent, 5 percent, and 10 percent significance levels, respectively. The reference group for the workers' tenure shares are workers with a tenure of up to 5 years; instead, for the age distribution, it is the share of young and prime-age workers; for the education distribution, it is the share of workers with a low education level; for the occupation distribution, it is the share of white-collar workers. The size dummies consist of three dummies, one for each size class, as in Table 1; the region dummies consist of three dummies, one for each administrative region in Belgium (Brussels-Capital, Flanders and Wallonia); the industry dummies account for 36 dummies, one for each 2-digit NACE Rev.2 industry; the year-industry dummies are based on 3-digits NACE Rev.2.
Source: SBS-SES data set (years: 2005-2016).

Table 4: The impact according to the workforce characteristics

	Coefficient	Standard error
Non-routine environments		
Mean tenure * Firms with a low-to-medium tenure (<12)	0.001	0.018
Mean tenure * Firms with a high tenure (≥12)	0.002	0.011
Observations: 1,896		
Routine environments		
Mean tenure * Firms with a low-to-medium tenure (<12)	0.011***	0.002
Mean tenure * Firms with a high tenure (≥12)	0.008***	0.001
Observations: 5,075		
Low-skilled environments		
Mean tenure * Firms with a low-to-medium tenure (<12)	0.025**	0.012
Mean tenure * Firms with a high tenure (≥12)	0.017***	0.006
Observations: 4,554		
High-skilled environments		
Mean tenure * Firms with a low-to-medium tenure (<12)	0.011*	0.006
Mean tenure * Firms with a high tenure (≥12)	0.013***	0.005
Observations: 2,417		

Notes: Estimation method: ACF-FE. We report firm-level cluster-robust bootstrapped standard errors. ***, **, and * denote the 1 percent, 5 percent and 10 percent significance levels, respectively. These estimates include the same set of controls as in Table 3. For the remaining ones, see the footnotes to Table 1 and Table 2.
Source: SBS-SES data set (years: 2005-2016).

Table 5: The impact according to the firm's characteristics

	Coefficient	Standard error
Industrial environments		
Mean tenure * Firms with a low-to-medium tenure (<12)	0.005*	0.003
Mean tenure * Firms with a high tenure (≥12)	0.004**	0.002
Observations: 4,585		
Non-Industrial environments		
Mean tenure * Firms with a low-to-medium tenure (<12)	0.001	0.014
Mean tenure * Firms with a high tenure (≥12)	-0.001	0.007
Observations: 2,386		
High Capital-Intensive environments		
Mean tenure * Firms with a low-to-medium tenure (<12)	0.005**	0.002
Mean tenure * Firms with a high tenure (≥12)	0.005*	0.003
Observations: 3,741		
Low Capital-Intensive environments		
Mean tenure * Firms with a low-to-medium tenure (<12)	0.012	0.009
Mean tenure * Firms with a high tenure (≥12)	0.004	0.004
Observations: 3,230		
ICT environments		
Mean tenure * Firms with a low-to-medium tenure (<12)	0.000	0.012
Mean tenure * Firms with a high tenure (≥12)	-0.001	0.007
Observations: 3,124		
Non-ICT environments		
Mean tenure * Firms with a low-to-medium tenure (<12)	0.026***	0.005
Mean tenure * Firms with a high tenure (≥12)	0.015***	0.004
Observations: 3,847		
Knowledge-Intensive environments		
Mean tenure * Firms with a low-to-medium tenure (<12)	-0.012	0.011
Mean tenure * Firms with a high tenure (≥12)	-0.009*	0.005
Observations: 1,398		
Non-Knowledge-Intensive environments		
Mean tenure * Firms with a low-to-medium tenure (<12)	0.007***	0.002
Mean tenure * Firms with a high tenure (≥12)	0.005***	0.001
Observations: 5,573		

Notes: Estimation method: ACF-FE. We report firm-level cluster-robust bootstrapped standard errors. ***, **, and * denote the 1 percent, 5 percent, and 10 percent significance levels, respectively. These estimates include the same set of controls as in Table 3. For the remaining ones see the footnotes to Table 1 and Table 2.
Source: SBS-SES data set (years: 2005-2016).

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Appendix

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

We here present a discussion on our empirical framework in the context of ACF and ACF-FE estimations. For details on the underlying assumptions - which we summarize hereafter - and their implications, the reader may refer to Ackerberg et al. (2015) and Lee et al. (2019).

We estimate the following augmented production function (we omit control variables for ease of exposition):

$$y_{it} = \alpha + \beta_l l_{it} + \beta_k k_{it} + \theta ten_{it} + \tau ten_{it}^2 + \omega_{it} + \varepsilon_{it} \tag{A.1}$$

First, it is assumed that the firm's information set at t, I_{it}, includes the 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}, cannot be predicted by the firm (i.e., $E[\varepsilon_{it}|I_{it} = 0]$).

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) implies 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, is not predictable at $t - 1$. In practice, firms observe ω_{it} at t and construct expectations about ω_{it} at $t - 1$ using $g(\cdot)$.

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 a full period is required 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 one period earlier, at $t - 1$, thereby allowing it to have dynamic implications. This is in line with the presence of significant rigidities on the Belgian labor market, such as hiring and firing costs (see the discussion on the Belgian labor market in Section 4).[24] Consistently, tenure is assumed to respond to productivity shocks with a one-period lag (i.e., tenure at t is set at $t - 1$).

Fourth, it is assumed that the firm's demand for intermediate inputs, m_{it}, is a function of labor, capital,

[24] See Konings and Vanormelingen (2015) for a similar assumption applied to the Belgian context.

tenure, and a firm's unobserved productivity level:

$$m_{it} = f\left(l_{it}, k_{it}, ten_{it}, ten_{it}^2, \omega_{it}\right). \tag{A.3}$$

Lastly, it is assumed that the function in (A.3) is strictly increasing in ω_{it}. Intuitively, this means that, conditional to labor, capital and tenure, the higher the unobserved productivity level is, the larger the demand for intermediate inputs. At this point, ACF outlines a two-step estimation method. Given the assumptions discussed above, f can be inverted to deliver an expression of ω_{it}, which is unobservable, as a function of l_{it}, k_{it}, ten_{it}, and m_{it}, which are instead observable:

$$\omega_{it} = f^{-1}\left(l_{it}, k_{it}, ten_{it}, ten_{it}^2, m_{it}\right).$$

The inverted intermediate input demand function $f^{-1}(\cdot)$ is the key to Control Function Estimation (CFE): it allows the unobserved productivity level to be "controlled" once inserted into the production function. Hence, substituting $f^{-1}(\cdot)$ in Equation (A.1) results in the following first-stage equation:

$$\begin{aligned} y_{it} &= \alpha + \beta_l l_{it} + \beta_k k_{it} + \theta ten_{it} + \tau ten_{it}^2 + f^{-1}\left(l_{it}, k_{it}, ten_{it}, ten_{it}^2, m_{it}\right) + \epsilon_{it} \\ &= \Phi\left(l_{it}, k_{it}, ten_{it}, ten_{it}^2, m_{it}\right) + \epsilon_{it}. \end{aligned} \tag{A.4}$$

As is common practice in the literature, we proxy the function Φ with a third-order polynomial in l_{it}, k_{it}, ten_{it}, ten_{it}^2, and m_{it} (Ackerberg et al., 2015). The parameters β_l, β_k, θ, and τ are clearly not identified at this stage and are subsumed into $\Phi\left(l_{it}, k_{it}, ten_{it}, ten_{it}^2, m_{it}\right) = \alpha + \beta_l l_{it} + \beta_k k_{it} + \theta ten_{it} + \tau ten_{it}^2 + \omega_{it}$. However, the estimation of (A.4) produces the estimate $\tilde{\Phi}\left(l_{it}, k_{it}, ten_{it}, ten_{it}^2, m_{it}\right)$ of $\Phi(l_{it}, k_{it}, ten_{it}, ten_{it}^2, m_{it})$.[25]

From given guesses of β_l, β_k, θ, and τ, denoted as β_l^*, β_k^*, θ^*, and τ^*, it is possible to recover the implied ω_{it}, $\tilde{\omega}_{it}(\beta_l^*, \beta_k^*, \theta^*, \tau^*)$[26], as:

$$\tilde{\omega}_{it}(\beta_l^*, \beta_k^*, \theta^*, \tau^*) = \tilde{\Phi}\left(l_{it}, k_{it}, ten_{it}, ten_{it}^2, m_{it}\right) - \beta_l^* l_{it} - \beta_k^* k_{it} - \theta^* ten_{it} - \tau^* ten_{it}^2. \tag{A.5}$$

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

$$\frac{1}{N}\frac{1}{T}\sum_i \sum_t \tilde{\xi}_{it}(\beta_l^*, \beta_k^*, \theta^*, \tau^*)\, k_{it} = 0$$

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

$$\frac{1}{N}\frac{1}{T}\sum_i \sum_t \tilde{\xi}_{it}(\beta_l^*, \beta_k^*, \theta^*, \tau^*)\, l_{it} = 0$$

$$\frac{1}{N}\frac{1}{T}\sum_i \sum_t \tilde{\xi}_{it}(\beta_l^*, \beta_k^*, \theta^*, \tau^*)\, ten_{it} = 0 \quad (A.6)$$

$$\frac{1}{N}\frac{1}{T}\sum_i \sum_t \tilde{\xi}_{it}(\beta_l^*, \beta_k^*, \theta^*, \tau^*)\, ten_{it}^2 = 0 \quad (A.7)$$

The search over β_l^*, β_k^*, θ^*, and τ^*continues until $\widetilde{\beta_l}$, $\tilde{\beta}_k$, $\tilde{\theta}$, and $\tilde{\tau}$ are found, in order to the satisfy Equations (A.6 – A.7). These are the ACF estimates of β_l, β_k, θ, and τ.

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

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

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

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

According to the above specification of ω_{it}, the first step of the ACF-FE procedure is the same as in ACF, except for the addition of 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. In the second stage, it is possible to estimate β_l, β_k, θ and τ by 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 the implied ω_{it} as in (A.5) and then the implied ξ_{it} as the residuals of a fixed effects regression of $\widetilde{\omega}_{it}$ on $g(\widetilde{\omega}_{it-1})$, with $g(\cdot)$ approximated by means of a third-order polynomial (Lee et al., 2019).