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The kind of things that money just can't buy: The role of potential absorptive capacity in enhancing firm-level employment growth

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ABSTRACT

This study provides new firm-level evidence on the impact of the technological change generated by investments in instrumental goods on employment growth. We posit that firms' potential absorptive capacity moderates this effect by leveraging the embodied technological change (ETC) contained in these goods. Testing our hypothesis on administrative linked employer-employee (LEED) data for a sample of 6.120 manufacturing firms over 2008–2017, we find that ETC investments have an overall positive and significant effect on employment growth. Such an effect depends on firms' technological intensity and size class, with a larger impact on high-tech and large firms. However, higher levels of potential absorptive capacity increase positively and significantly the effect for low-tech and SMEs in a way that is more compatible with a conditional role than a moderating one. Our findings imply that regional policies should consider firm-specific investments targeted to human capital accumulation and collaborative partnerships to maximize the occupational impact of ETC investments.

1. Introduction

The debate on the socio-economic effects of technological change is a long-standing issue across different research fields. Currently, a new wave of interest is driven by the unintended consequences of the key enabling technologies of Industry 4.0.[1] Advances in ICT, automation, and digitalization of industrial production deeply impact the occupational structure of labour forces, nature of labour, and demand for skills, generating at the same time opportunities and uncertainty about the future of work (Brynjolfsson and McAfee, 2014; Arntz et al., 2016; Frey and Osborne, 2017; Ayhan and Elal, 2023).

Does technological change complement or substitute for human labour? In the last decades, the issue has been largely investigated and is at the forefront of academic and policy debate at the international level due to the social and economic consequences of such changes. The reason for such concern is justified by the intrinsic difficulty in estimating the overall socio-economic impact, the rapidity of such transformations, and the need to design new economic policies to adapt to this phenomenon.

From a theoretical point of view, one of the key issues is to consider the two main sources of innovation: product innovation, based on investments in formal R&D, and process innovation associated with technological acquisition through investments in new machinery, equipment, and tools (Schumpeter, 1934; Dosi, 1984), often referred to as "embodied technological change" (henceforth ETC). In the empirical literature, there is broad consensus on the positive impact of product innovation on employment, whereas the available evidence on the role of process innovation is uncertain on its causal effects and not as largely investigated as the former. Generally, product innovation is often put in place via R&D efforts aiming at developing new products leading to economic growth and job creation, whereas process innovation is thought of as a labour-saving investment. However, labour-saving new techniques may well boost productivity, thus allowing price reductions and larger market shares with consequent economic and occupational growth at the firm level. At the macro level, compensation mechanisms may offset the total job destruction induced by the new technologies and increase job posts via income effects, new markets and investments, enhanced productivity, and international competitiveness. Different methodological issues arise when investigating these mechanisms, and the extent to which micro and macro compensations counterbalance the

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[1] Usually referred to also as the "Fourth Industrial Revolution," it encompasses all the transformations in the products and production processes related to the introduction of ICT, automation, artificial intelligence, internet of things and services, use of big data, and in general to the application of digital technologies.

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labour-saving nature of process innovation requires further scrutiny.

In this paper, we empirically verify that, following investments in ETC, positive effects prevail over substitution ones to the extent that firms can combine the external knowledge—embodied in the purchased instrumental goods—with their internal knowledge. This ability, referred to as "absorptive capacity" in both the economic and the management literature, is a function of "prior related knowledge and diversity of background" (Cohen and Levinthal, 1990). In this study, the absorptive capacity is thus proxied by the number of its "antecedents," which are "external sources of knowledge coming from acquisition and inter-organizational relations and internal sources, steaming from past experience and learning by doing" (Lewandowska, 2015).

Therefore, the aim of this paper is to investigate, at a firm level, the relationship between ETC and employment dynamics as mediated (conditioned) by the "antecedents" of absorptive capacity. This research adds to the discussion on the following aspects: first, it contributes to the debate on the labour-saving nature of ETC, investigating, for the first time, the role played by the absorptive capacity of firms; second, it sheds light on the relationship between absorptive capacity and employment at a micro level, that has been only scarcely investigated up to now[2]; Third, we provide results exploiting the unique feature of the administrative Linked Employer-Employee Data (LEED) of the Italian Emilia-Romagna region, analysing the wide aggregate of firms over a longer period and taking into account additional workers' and firms' characteristics compared to previous studies.

Our results reveal that ETC has a positive and significant effect on employment variations and a differential impact when estimated on subsamples identified according to the technological intensity and size class: positive and significant for high-tech firms. However, absorptive capacity is crucial in explaining this relationship, especially for low-tech and SMEs.

The remainder of the paper is organized as follows: the next section introduces the conceptual framework of the innovation-employment issue, illustrates the relevant literature in line with our approach, and explains the role of absorptive capacity and the hypothesis driving this study. Section 3 illustrates the data and provides basic statistics, while Sections 4 and 5 present the empirical approach and discuss the results, Section 6 discusses robustness check. A summary of the research concludes the paper and briefly discusses the relevant policy implications.

2. Background studies

In economic theory, the relationship between innovation and employment is a long-standing issue, with initial discussions originating from Smith, Ricardo, and Marx in response to the challenges posed by the first industrial revolution. This issue further developed with the following stages of massive technological advances in manufacturing production and the evolution of capitalist societies, which inevitably generated both opportunities and threats in the labour market, at least in the short run, in response to the rapid changes in the demand for goods and needs.[3] Typically, when addressing this issue, two contrasting visions emerge (see Freeman et al., 1982; Vivarelli, 1995). The *compensation* framework is in favour of the indirect effects of technological change, that is, of market compensation forces that would counterbalance the destruction of jobs in the long run. On the other side, the *substitution* framework is hinged on the labour-saving nature of innovation and states that it creates, as a direct consequence, technological unemployment through the automatization of productive processes that would displace the labour force. Within the *substitution* framework, further developments concerned the nature of technological change and explored its qualitative effect, suggesting that technological change only substitutes certain types of *skills* and *tasks*, thereby displaying heterogenous effects on workers depending on their level of endowments and capabilities, and the level of task routine. These advances refer to the Skill-Biased Technological Change (SBTC) and the Routine-Biased Technological Change (RBTC) hypotheses, which have dominated the research landscape in the recent decades. For a comprehensive recent review of theory and evidence, see Mondolo (2022).

2.1. Process innovation, ETC, and employment

The effect of innovation has long been debated and investigated following two main criteria, namely, the proxy for technological change (process vs product innovation) and the level of analysis (micro, sector, macro). The conceptual framework of this research is grounded on the innovation literature that focuses on the distinction between product and process innovation. Although these innovations are closely interlinked and coexist within firms, they have different objectives and may lead to different impacts on employment. The former mainly involve innovative activities to improve the quality of goods and services and widen their variety through investments in design and R&D, to create new opportunities and gain market shares. On the other side, process innovation is more related to the efficiency of the production process and is associated with investments in technological change to reduce costs and introduce flexibility in production.

In general, the empirical evidence seems inconclusive about the impact. Different contributions concentrated specifically on collecting and reviewing the significant number of empirical studies on this topic, to update and systematise the evidence produced so far (e.g., Vivarelli, 2014; Calvino and Virgillito, 2018; Mondolo, 2022). Results range from positive to adverse effects, and the impact may vary significantly according to the methodology, data, and countries. A recent meta-regression analysis, based on studies estimating derived labour demand models, indicate that innovation's effect on employment is positive, but small and highly heterogeneous (Ugur et al., 2018). Product innovation is often associated with the idea that "new products open up new markets, leading to job creation", especially during rapid growth phases, thus engaging in a "technological competitiveness" strategy mainly pursued with design and R&D activities. In contrast, process innovation consists "in a strategy of cost (or price) competitiveness" where "labour-saving new processes and organizations are introduced, leading to job losses" (Pianta, 2018, p.3).

However, even when defined in this minimal fashion, process innovation is suitable to bring about a vast gradient of different outcomes in terms of the variation of total employment at the firm, sectoral and macroeconomic levels. For instance, firms introducing labour-saving process innovation can be expected to substitute labour with capital goods and, at the same time, benefit from productivity gains enabling price reduction, thus leading to market share gains, faster growth, and, ultimately, hirings and job creation. At a macro level, compensation mechanisms may offset job losses via price reduction, enhanced international competitiveness, new machines and investments, and income effects. At a sectoral level, process innovation derived from innovative capital goods can constitute a source of simultaneous job creation and destruction. These goods operate as labour-saving innovations in the firms/sectors purchasing them as capital goods and as product innovation in firms (and sectors) producing them (Edquist et al., 2001).

So far, the issues related to the labour-saving or labour-friendly nature of process innovation seem to be far from fully disentangled, as

[2] Innovation literature focused mainly on the macro level (Findlay, 1978; Narula, 2004), whereas at the micro level, the focus has been set on the linkages between this capacity and innovativeness or on more conventional firm growth measures (e.g., sales and profits) in the management and organizational literature.

[3] On this point, Schumpeter (1961) claimed that "The fundamental impulse that sets and keeps the capitalist engine in motion comes from the new consumers' goods, the new methods of production or transportations, the new markets, the new form of industrial organization that capitalist enterprise creates".

remarked by Dosi and Mohnen (2019). Several recent studies addressed these issues at firm and sectoral levels across different countries and with different approaches. Therefore, given the bulk of studies produced on this topic, we briefly introduce the relevant evidence from longitudinal studies in line with our empirical approach. Among these, Lachenmaier and Rottmann (2011) find a positive impact of both product and process innovation for a panel of German manufacturing firms, with higher effects of innovation processes on employment variations. In contrast, results from Barbieri et al. (2019) reveal that R&D expenditures generating product innovation are likely to be labour-friendly, although limited to high-tech sectors and larger firms, and process innovation might also have a labour-destroying nature. Similarly, results from a sample of Spanish manufacturing firms in Pellegrino et al. (2019) reveal no significant effect of R&D and investment in innovative machineries and equipment on employment. Instead, Ciriaci et al. (2016) provide evidence of a positive impact on employment growth for more innovative, smaller, and younger Spanish firms, while Bogliacino et al. (2012) find a positive impact of R&D expenditure on employment level only for high-tech and service sector. More ambiguous evidence is found in Greenan and Guellec (2000). Results from this study show that more innovative firms contribute to creating new jobs than non-innovative firms, but the reverse trend is found when investigating at the sectoral level. Finally, Yang and Lin (2008) point to a positive and significant impact of both process and product innovation on a sample of Taiwanese firms, although the effect of process innovation may differ between high and low R&D-intensive industries when analysing different subsamples.

Table 1 synthesizes findings from different studies exploring the nexus between innovation and employment, drawing on Barbieri et al. (2019), Ciriaci et al. (2016), and Mastrostefano and Pianta (2009). Employing varied estimation methods, such as fixed effects and quantile regression, the research underscores a nuanced relationship. While some studies, like Barbieri et al. (2019), highlight positive impacts of innovation on employment, particularly among high-tech firms, others, like Mastrostefano and Pianta (2009), reveal mixed effects, including labour displacement from process innovation. Moreover, the unit of analysis varies, spanning from firm-level investigations, as in Ciriaci et al. (2016), to sector-level analyses, as in Mastrostefano and Pianta (2009). Overall, this diversity of findings highlights the need to consider sectoral contexts and temporal dynamics when exploring the employment implications of innovation.

Taken as a whole, the idea that ETC plays a differential role according to firms' size and sector is a result consistent with the existing evidence. However, management and organizational literature results suggest further room for research on this topic. It is reasonable to expect that other specific factors concur in shaping the impact of process innovation on employment, thus explaining the additional heterogeneity among peers, i.e., firms of the same size operating in the same industry.

2.2. *Absorptive capacity*

The extent to which firms benefit from purchasing new capital goods, embodying at least *new-to-the-firm* knowledge, depends on their capacity to deal with external knowledge, thus combining it with the internal one. Borrowing from the strategic management and organization theory literature, absorptive capacity (henceforth ACAP) is defined as "the ability of a firm to recognize the value of new, external information, assimilate it, and apply it to commercial ends" and is crucial for innovative activities to succeed (Cohen and Levinthal, 1990). Thus, a firm's potential ability to combine external and internal knowledge is also believed to maximize the innovative potential embodied in the

Table 1
Background studies.

Study	Country	Time period	Estimation method	Main results	Innovation type
			Unit: micro (firms)		
Barbieri et al. (2019)	Italy	1998–2010	FE-OLS	(+) R&D expenditures are labour-friendly for high-tech and larger firms. (−) process innovation might have a labour-destroying nature	Product and Process
Bogliacino et al. (2012)	OECD	1990–2008	LSDVC	(+) Impact of R&D on employment level only in services and high-tech firms	R&D
Ciriaci et al. (2016)	Spain	2002–2009	Quantile regression	(+) On employment growth for more innovative, smaller, and younger firms	Process
Greenan and Guellec (2000)	France	1985–1991	OLS	(+) On employment growth for more innovative (reverse trend is found when analysing at sectoral level)	Product and Process innovation
Lachenmaier and Rottmann (2011)	Germany	1982–2002	GMM	(+) Effect of process (higher than product innovation)	Product and Process innovation
Yang and Lin (2008)	Taiwan	1997–2003	GMM	(+) Impact of process and product innovation on firms (the effect differs depending on R&D sector intensity)	Product and Process innovation
Pellegrino et al. (2019)	Spain	2002–2013	GMM	No effect of R&D and process innovation on employment	Product and Process innovation
Stam and Wennberg (2009)	The Netherlands	1994–2000	OLS	No effect of R&D on employment growth. (+) effect on top 10 % and high-tech	R&D
			Unit: *meso* (sectors)		
Bogliacino and Vivarelli (2012)	Europe	1996–2005	GMM	(+) R&D expenditure have a job-creating effect	R&D
Buerger et al. (2012)	Germany	1999–2005	LAD estimation	(+) Impact of patents on employment	Patents, R&D
Conte and Vivarelli (2011)	Low-Middle income countries	1980–1991	GMM	Increase in relative demand for skilled workers	ICT
Dosi et al. (2021)	Europe	1998–2016	FE-GMM	No significant effect of embodied and disembodied technological change	Product and Process
Lucchese and Pianta (2012)	OECD	1995–2007	WLS	Innovation-based growth and employment dynamics operate in different ways over the business cycle.	Product and Process
Mastrostefano and Pianta (2009)	Europe	1994–2000	OLS	(+) Effect of demand growth (−) role of wage changes and limited effects from the general diffusion of innovation. (+) role of the market impact of product innovation	Product

purchased machinery (Zahra and George, 2002; Todorova and Durisin, 2007; Schilke, 2014).

In our case, the more a firm is used to searching for external knowledge and combining it with its internal knowledge and routines, the more likely process innovations will succeed. In fact, the type of process innovation under scrutiny is represented by ETC that can be disembodied by leveraging ACAP, which in turn is augmented through the breadth of external knowledge search, internal and inter-organizational firms' resources (Cohen and Levinthal, 1990). Following this approach, it can be argued that the presence of a set of activities capable of determining the development of innovative, dynamic capabilities (in this case, the "antecedents" of ACAP) can account for a firm's ability to combine external and internal knowledge to maximize the innovative potential embodied in the purchased machinery (Zahra and George, 2002; Todorova and Durisin, 2007; Schilke, 2014). For the sake of our exploration, we define *antecedents* following Lewandowska (2015), who describes them as "external sources of knowledge coming from acquisition and inter-organizational relations and internal sources, steaming from past experience and learning by doing". Indeed, following Zahra and George's (2002) seminal distinction between 'potential' and 'realized' ACAP, Franco et al. (2014) found evidence of the positive relationship between antecedents, a residual measure of potential ACAP, and its impact on innovation (for a recent review and meta-analysis, see Zou et al., 2018).

Given the multi-dimensional nature of dynamic and absorptive capacity, a wide stream of management and organizational literature has developed several ways to measure these concepts, focusing on economic and innovation activities and other social and relational characteristics of firms and employees. The combination of different determinants of potential ACAP into composite scales of inputs has emerged as a practical approach to proxying these dynamic capabilities (Szulanski, 1996; Lane et al., 2001; Lin et al., 2002; Jansen et al., 2005; Nieto and Quevedo, 2005). In our study, firms' potential ACAP is thus proxied by an input measure based on the number of *antecedents* that firms exploit among the following dimensions: R&D activities, education level of employees, participation into research networks, level of VA over sales ratio, outsourcing practices, export capacity, firms' experience, and specialization.

The idea that ACAP is suitable to ease the catch-up of countries and regions that are lagging in terms of innovativeness, competitiveness, and even employment rates and economic growth is not new, although investigated mainly at the macro level and for developing countries (Findlay, 1978; Narula, 2004; Fagerberg, 2005). Concerning firms, ACAP is usually associated with its importance for low-tech and middle-low-tech firms to make productive use of the last development usually generated in the "upstream" sectors, i.e., high-tech (Cohen & Levinthal, 1989; 1990; Von Tunzelmann and Acha, 2005). Education of the workforce, efforts in the search, processing, and commercial exploitation of external knowledge, R&D activities, formal and informal networks, and collaborative agreements are all factors (*antecedents*) capable of enhancing the ability of a firm to benefit from public resources represented by knowledge, making it easier for innovative efforts to succeed and thus favouring knowledge transfers, technological flows and spill overs (Cohen and Levinthal, 1989, 1990; Powell, 1996; Cantwell, 2005; Narula and Zanfei, 2005; Moilanen et al., 2014).

Hence, the differential employment impact of the process innovation depending on firm size suggests that ACAP may play a pivotal role in shaping the relationship between ETC and the employment dynamics of firms. From a theoretical point of view, it is reasonable to assume that the ability to combine external and internal knowledge can be leveraged to maximize benefits from the innovative potential embodied in the purchased machinery. On the other hand, all the *antecedents* capable of developing ACAP are asymmetrically distributed across firm-size classes: R&D activities, participation in networks, and human capital accumulation strategies, for instance, require relatively more complex organizational structures, characterized in turn by considerable financial resources and managerial expertise which are hardly met in SMEs. Therefore, large firms tend to have higher ACAP levels because they are more likely to engage in R&D activities, have relatively more qualified labour forces, and connect with both foreign and domestic science bases (Narula and Zanfei, 2005).

2.3. Research questions and rationale of the study

Grounding on this conceptual framework, the main novelty of our study is to estimate the effects of the investments in embodied technological change (ETC) on employment variations at a firm level examining the role played by ACAP, as proxied by the breadth of its antecedents. In addition, the paper exploits the Linked Employer-Employee Data (LEED) that allows working with a large sample of observations, considering firms' and workers' characteristics alike. To this aim, we arrange the empirical analysis to answer the following research questions:

RQ 1 – Does Embodied Technological Change (ETC) have a labour-saving or labour-friendly nature? Does it have a differential impact according to size and sector?

RQ 2 – In case this differential impact is confirmed, is it mediated (conditioned) by firms' ability to combine internal and external knowledge?

Our main hypothesis is that, besides compensation mechanisms and workforce composition, the differential effect of ETC is mainly explained by firms' capacity to combine external and existing internal knowledge. We support the theory that innovation is a highly differentiated process with innovative activities and strategies that vary among firms, products, sectors, and different local institutional contexts. Several factors affecting the firms' ability to combine internal and external knowledge should play a consistent role in shaping the occupational effects of technological change. In addition, while there is a vast and heterogeneous literature investigating firm growth and its possible determinants, such as age and size (Dobbs and Hamilton, 2007; Coad, 2009), business performance (Foster et al., 1998; Bottazzi et al., 2010) and/or innovative activities such as R&D (Audretsch et al., 2014; Oliveira and Fortunato, 2017), scant attention has been devoted to the potential effects of this dynamic capacity. Studies investigating ACAP mostly focus on innovative outcomes or conventional measures of business performance such as sales growth, profit, and other economic variables (Chesbrough et al., 2006; Laursen and Salter, 2006), and innovativeness as a whole (Moilanen et al., 2014) rather than employment impacts. Finally, studies addressing this issue are usually focused on the macro level (Findlay, 1978; Narula, 2004).

Our study aims at filling this gap by regressing employment growth at a firm level on the interaction among innovative efforts (i.e., ETC investments) and the antecedents of absorptive capacities. In our expectations, the higher the number of antecedents, the higher the positive effect of ETC on employment growth as firms increase the probability of success of their innovative efforts, thus pursuing a comparative advantage and paving the way to economic and employment growth.

3. Data and descriptive statistics

In this paper, we use a unique source of Linked Employer-Employee Data (LEED), the "*Sistema Informativo Lavoro - Emilia Romagna* (*SILER*)".[4] This regional archive collects administrative labour market microdata for all employees in the Italian Emilia-Romagna region starting from 2008. The system is based on compulsory communications that employers must file for each occurrence in all employment relationships in

[4] *SILER* archive is provided by the regional company ART-ER and authorized for research purposes, under approval n.554, by Emilia Romagna region (regional Agency for Employment) within the research project *COME - Competence for Manufacturing in Emilia Romagna* (Emilia Lab).

Table 2
Panel composition.

Year	Full sample	SME < 250	Large ≥ 250	Low-Tech	High-Tech
2008	2.130	1469	661	1260	870
2009	1.997	1333	664	1173	824
2010	1.976	1301	675	1153	823
2011	1.895	1193	702	1120	775
2012	1.931	1220	711	1113	818
2013	1.980	1255	725	1136	844
2014	3.767	3007	760	2312	1455
2015	4.089	3282	807	2521	1568
2016	3.098	2266	832	1870	1228
2017	3.702	2820	882	2259	1443
Total	26.565	19.146	7.419	15.917	10.648

Notes: frequency refers to the number of observations in the panel. Size classes are calculated on the annual labour unit "ULA."

the private sector concerning salaried occupations, except for agency contracts.[5] The peculiar feature is the collection of a detailed set of information that refers to the job positions started, transformed, extended, and ended in the period for both employees and employers. In particular, *SILER* provides administrative information concerning employees' characteristics (age, gender, educational attainment) and working experiences (employers, type, and duration of contracts). As far as firms are concerned, the total labour force, our dependent variable, is measured in terms of full-time equivalent employees (FTE), calculated based on the workers' actual presence on the post annually. In addition, we extended this set of information with balance sheet data from *Aida* (Bureau Van Dijk), organizing a unique panel dataset of manufacturing firms with positive values for value-added and turnover that operated between 2008 and 2017 in the Emilia-Romagna region. The final dataset was obtained by excluding firms with no valid records for FTE total labour force, intangible assets, production costs, sales, firm age, educational attainments of their employees, median age of the labour force, median value for years of working experience, median tenure, expenses in machinery, equipment and tools thus resulting in an unbalanced panel of 26.565 observations (6.120 firms), as shown in Table 2 below.

Our focal regressor is "Antecedents," a count measure that is built on a 1 to 7 points scale based on the number of items deployed by the firm, operationalized as dummy variables, in the following list:

- The presence of R&D activities in the year of interest (if R&D activities are in place, the relative dummy variable equals 1 and 0 otherwise). For similar approaches, see Cohen and Levinthal (1990), Tsai (2001), and Zahra and Hayton (2008). The presence of continued R&D activities is widely regarded as a source of ACAP development both in the management and innovation economics literature.
- High share of graduate employees on total employment (i.e., if the share of graduate workers on the firm's total employment is above the average share of graduates on the total labour force in the sample in the year of interest, the relative dummy equals 1 and 0 otherwise). See Cohen and Levinthal (1990), Muscio (2007), and Moilanen et al. (2014) for similar approaches. The quality and accumulation of human capital are considered crucial in the development of ACAP at both macro and micro levels (Findlay, 1978; Narula, 2004; Narula and Zanfei, 2005).
- Participation in formal research networks established or recognized by public research institutes (with the relative dummy equal 1 if the firm is participating and 0 otherwise). Absorptive capacity has been proxied in this manner by Mangematin and Nesta (1999), George et al. (2001), and Arvanitis and Woerter (2009). Collaboration and participation into networks are crucial in training the capabilities needed to combine internal and external knowledge (Franco et al., 2014), and it is often associated with R&D activities (Cohen et al., 1989; Powell, 1996).
- Quality production and value creation (i.e., if value added over sales ratio is above the average of the sample in the year of interest this dummy equals 1 and 0 otherwise). For a similar approach, see Zahra and George (2002).
- Outsourcing practices as opposed to the "not invented here syndrome" (i.e., if the ratio between outsourcing spending on total production costs is above the average in the sample in the year of interest, the relative dummy equals 1 and 0 otherwise). On this point, see Azadegan (2011).
- Firms' capacity to export (i.e., the relative dummy equals 1 if the firm is registered as an export operator, and 0 otherwise). See Brandt et al. (2012).
- Experience and specialization of firms as measured by the share of its tenured employees (i.e., if the share of tenured employees on the firm's total employment exceeds the relative average share in the total labour force in the year of interest, the relative dummy equals 1, and 0 otherwise). See Cohen and Levinthal (1990).

Fig. 1 illustrates the quantile distribution of potential ACAP expressed by its antecedents. Firms in the lower quartile are identified as "low-potential" and represent about 25 % of the whole sample (having 0 or 1 item), while firms in the upper quartile are identified as "high-potential" (having from 4 to 7 items).

Table 3 displays the main variables used in the econometric specification and reports basic statistics for the final sample of firms and three subsamples displaying high, medium, and low firms' innovative potentials in terms of absorptive capacities, as proxied by the number of antecedents deployed at a firm-level in each year. Our second focal regressor is ETC, which we measure with a proxy, namely the total

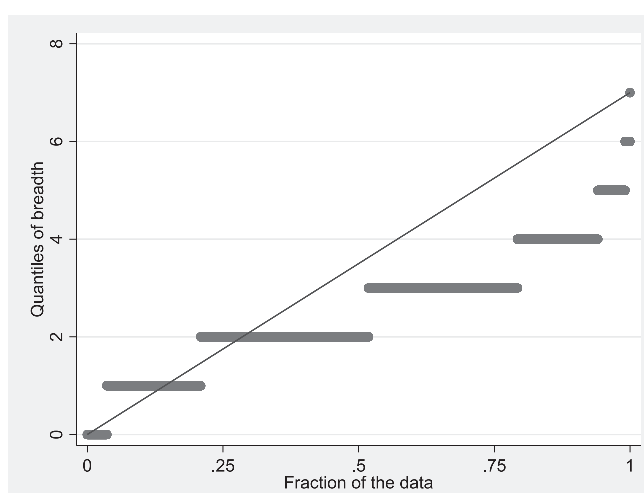

Fig. 1. Quantile distribution of antecedents.
Notes: the distribution refers to 1 to 7 points scale based on the number of items deployed by the firm.

[5] Excluding agency contracts might introduce a bias in our measure. However, it is worth stressing that such contracts represented a very limited fraction of the Italian labour force that evolved similarly to overall employment over 2008–2017 (see Ciucciovino et al., 2022). Moreover, since a major reform occurred in 2016 (i.e., the "Jobs Act") we reiterated all estimates excluding years 2016 and 2017 thus further testing the robustness of our results. The estimates are not included in the article for brevity and are available upon request.

Table 3
Descriptive statistics: different ACAP potentials.

	Full sample		High potential		Others		Low potential		F test
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	
Total employment (ln)	3.43	1.21	3.78	1.15	3.39	1.21	3.05	1.15	***
ETC (ln)	4.77	1.63	5.15	1.61	4.74	1.63	4.33	1.53	***
Breadth	2.61	1.26	5.15	0.37	2.83	0.77	0.82	0.38	
Value added (ln)	7.77	1.41	8.21	1.33	7.71	1.42	7.34	1.32	***
Labour productivity (ln)	4.34	0.60	4.43	0.57	4.32	0.61	4.29	0.60	***
Labour cost (ln)	3.94	0.44	4.03	0.44	3.93	0.45	3.83	0.41	*
Value added/sales (ln)	−1.37	0.55	−1.29	0.54	−1.32	0.52	−1.70	0.59	***
Immaterial assets/total assets	0.14	0.21	0.15	0.21	0.14	0.21	0.11	0.18	***
Firm age	3.01	0.78	3.23	0.60	2.95	0.80	2.90	0.83	***
ROI	0.09	0.18	0.09	0.09	0.09	0.22	0.07	0.13	***
Capital intensity	10.81	1118.71	2.38	5.38	16.16	1436.81	2.87	7.59	***
Workers' median age	0.13	5.13	0.87	4.78	0.03	5.16	−0.58	5.34	*
Workers' median experience	10.89	27.27	12.20	28.77	10.52	28.37	10.37	19.58	***
Share of tenured workers/sample average	0.49	0.50	0.58	0.49	0.54	0.50	0.19	0.39	***

Notes: employment is expressed in annual labour units "ULA" and measured as full time equivalent (FTE), as used by the Italian National Institute of Statistics ISTAT. F-tests significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

expenses in industrial plants, machinery and tools of firm *i* at time *t*. This approach is very similar to that implemented by Barbieri et al. (2019), who measured ETC as "Innovative expenditures devoted to the acquisition of machinery, equipment, and software (excluding expenditures on equipment for R&D)" by drawing on CIS data. However, there are at least three important differences that need to be taken into account. First, we base our measure on balance sheet data rather than on self-reported figures in ad-hoc surveys. This circumstance is expected to sensibly improve the precision and reliability of our figures across the board; on the other hand, it is not possible to assess the specific 'innovative' nature of such expenditures. To address this concern, we implement and report in Section 6 estimates obtained using an alternative proxy measure for expenses on innovative industrial plants, machinery and equipment/tools based on CIS data. Second, R&D expenditures cannot be reliably inferred from balance sheet data due to inconsistencies across different types of firms in reporting duties due to Italian laws. As a consequence, we cannot deduct expenditures on equipment for R&D from investments and can only ascertain whether firm *i* does carry R&D activities at time *t* or not. Third, since we use balance sheet entries, which represent the accumulated stock of industrial plants, machinery and equipment rather than expenditures occurring in a single financial year, we conduct (and report in Section 6) a specific robustness check to account for depreciation. On the other hand, relying on the stock of machinery for our estimates is not a concern within the framework of our empirical exercise. This approach is supported by panel fixed-effects estimates that emphasize within-individual variations over time, thereby capturing sales and purchases.

We find that different potentials in terms of absorptive capacities are associated with significant differences at the firm level. High-potential firms are larger and older compared to low-potential ones, with higher levels of labour productivity, labour costs, and more experienced employees. Finally, the last column shows the result of F-tests differences in means between the different groupings of firms.[6]

Fig. 2 illustrates the evolution of a measure of performance (total sales) and total employment (measured in terms of full-time equivalent employees) for the two extreme quartiles. It is worth noting how high and low-potential firms tended to grow over the years, although with different patterns. On the left side, total sales for high and low-potential firms in absolute terms display a shared growth pattern until 2011, followed by a diverging one afterward, with high-potential firms' growth sales significantly higher. Regarding total employment, all firms' groupings grew differently during the period. In absolute terms, "high-potential" firms increased from about 35k to 39k FTE employees (+10.1 %), and "low-potential" from 11k to 15k (+37.1 %), whereas firms in the "Others" grouping grew the most, from about 61 k to 85 k (+38.9 %).[7] In relative terms, we observe—in the right-side graph—an increased average employment in the "high potential" firms, while for "low-potential" firms remained constant (for further details, see Table 3A in the Appendix).

Firms with high potential in terms of ACAP may be characterized by relatively more complex organizational structures being larger, more productive, and with higher labour costs. Fig. 3 confirms this insight showing a growing ACAP potential based on firms' age. In fact, only a small fraction (7.9 %) of firms less than three years old shows high potential, whereas this share raises up to 26 percentage points in firms over ten years old. This is especially true for strategies linked to the accumulation of human capital that require suitable managerial skills, which, in turn, can be developed only over time (Arrighetti et al., 2021). Consequently, the older the firm, the higher the ACAP potential.

As far as size is concerned, as the graph on the left shows, firms with low ACAP potential are frequent in the size class 0–9 employees (23.1 %) and tend to decrease with size, with only a small fraction of firms over 250 employees (7.4 %) characterized by low potential. On the contrary, ACAP potential tends to grow with size, with only 12.7 % of firms with less than ten employees falling in the higher quartile of ACAP antecedents and a relative majority of firms over 250 employees (35.0 %) falling in the same category. This is in line with the existing literature that shows higher ACAP in larger firms as these latter are more likely to engage in activities suitable to enhance firms' capabilities (e.g., R&D).

Moreover, firms operating in more innovative sectors displaying relatively higher technological intensity levels are more likely to engage in R&D activities and invest in human capital accumulation, thus boosting ACAP (Cohen and Levinthal, 1990; Tsai, 2001; Zahra and Hayton, 2008). Fig. 4 shows ACAP potential across the categories of the Pavitt taxonomy. It is worth noting, as expected, that high potential increases with technological intensity across groups: *supplier-dominated* (16.2 %), *scale-intensive* (22.3 %), *specialised-suppliers* (29.1 %), *and science-based* (32.9 %).

Interestingly, a degree of heterogeneity characterizes groups as firms with high (low) potential coexist in each category. However, ACAP tends to be more frequent in high-tech firms, reducing the relative

[6] For a complete description of the variables and the correlation matrix, see Tables 1A and 2A in the Appendix.

[7] These changes, however, were determined by a tendency of small and medium firms in the upper quartile to reduce the number of items deployed, thus determining a shift from the "high potential" cluster to the "others" one. This, in turn, resulted in increased average employment in the "high potential" firms.

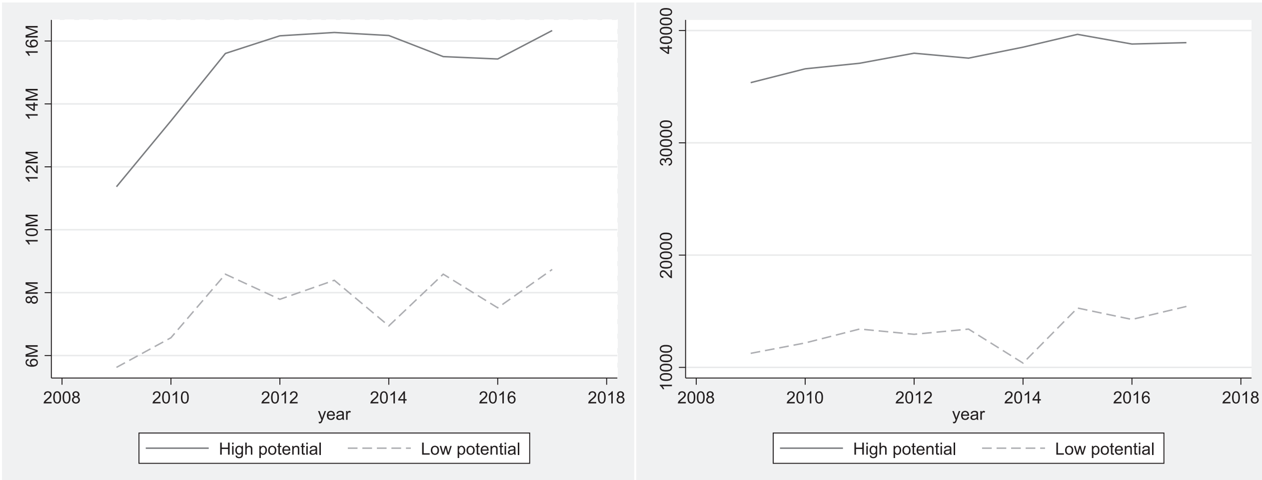

Fig. 2. Total sales and mean total employment by potential absorptive capacity.
Notes: "Low potential" and "High potential" are defined as firms endowed with 0–1 antecedents and 4–7 antecedents, respectively.

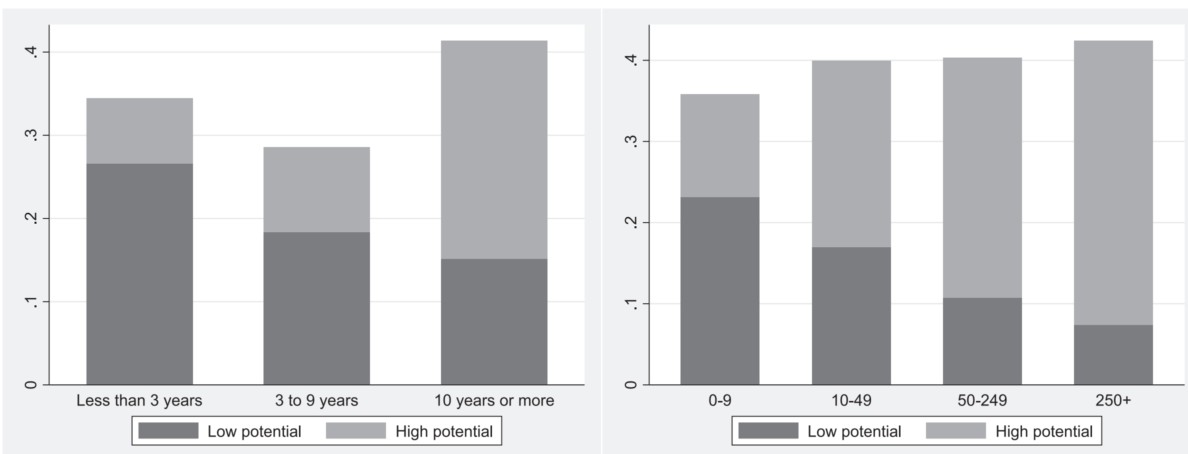

Fig. 3. Share of firms by potential absorptive capacity and firm age and size classes.
Notes: "Low potential" and "High potential" are defined as firms endowed with 0–1 antecedents and 4–7 antecedents, respectively.

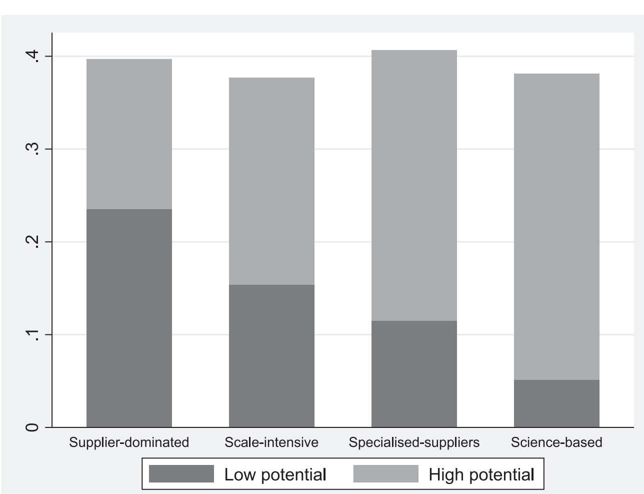

Fig. 4. Share of firms by potential absorptive capacities and Pavitt sectors.
Notes: "Low potential" and "High potential" are defined as firms endowed with 0–1 antecedents and 4–7 antecedents, respectively.

heterogeneity of this group. In a specular way, low-potential firms dominate Pavitt 1, characterized by traditional, price-sensitive productions.

4. Econometric analysis

We address our RQs and verify the effects of process innovation on employment variation over the period 2008–2017 with different specifications and samples, controlling with a large set of control variables for firms' characteristics (labour productivity, labour cost, ROI, value added over turnover, intangible assets, firm age, capital intensity), human capital endowments (labour force education, age, tenure, and working experience) and time effects. To this aim, our baseline specification is represented by a fixed effect model as the following:

$$Empl_{i,t} = \alpha + \beta_1 ETC_{i,t-1} + \gamma X_{i,t-1} + \delta_t + \varepsilon_i \text{ with } i = 1, \ldots, N; t = 1, \ldots T \tag{1}$$

where the dependent variable (*Empl*) is measured as the natural logarithm of the firm's total employment (FTE) and thus captures the variation in employment levels for each firm *i* over time *t*; β_1 is the coefficient of our proxy of process innovation (*ETC*), $X_{i,t-1}$ is a vector of control variables, while δ_t includes time dummies for common shocks and ε_i is the error term. To check whether there are differences in the

Table 4
Fixed Effects (FE) ETC gross of depreciation - 2008–2017.

	(1)	(2)	(3)	(4)	(5)
	All	Hitech	Lowtech	SMEs	Large
ETC_{t-1} (ln)	0.016***	0.025***	0.007	0.015**	0.054***
	(0.005)	(0.007)	(0.009)	(0.006)	(0.020)
Constant	0.157	0.555***	−0.066	0.173	1.846***
	(0.140)	(0.167)	(0.207)	(0.139)	(0.618)
Observations	17,578	7240	10,338	16,887	691
R-squared	0.570	0.573	0.577	0.558	0.585
Number of id	3972	1516	2456	3900	114
Time dummies	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses; Significance levels: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

extent to which process innovation affects employment at the firm level, we iterate estimates on different subsamples: high-tech and low-tech firms, SMEs and large firms. In fact, a potential issue arising from our approach is represented by endogeneity due to reverse causality and/or omitted variable. To partially mitigate this issue, we resort to panel FE estimates. In fact, by into account individual FE, we rule out the influence of possible unobserved time-invariant characteristics and make our regressor and controls predetermined with respect to the dependent variable by including them in the model with a 1-year lag.

Then, we iterate the analysis to check whether the occupational effect of expenses in innovative machinery (ETC) is mediated (conditioned) by ACAP (as proxied by antecedents). To this aim, we include in our model the composite measure of the potential ACAP of the firm along with the interaction with ETC.

$$Empl_{i,t} = \alpha + \beta_1 ETC_{i,t-1} + \beta_2 ANT_{i,t} + \beta_3 ETC_{i,t-1} {}^* ANT_{i,t} + \gamma X_{i,t-1} + \delta_t + \varepsilon_i \quad (2)$$

where $ANT_{i,t}$ is the number of antecedents deployed by firm i at time t. By doing so, we are able to assess the extent to which employment dynamics are determined solely by ETC, antecedents of ACAP or a combination of both.

5. Empirical evidence

Table 4 shows Fixed-Effects (FE) estimates from the whole manufacturing sample and two sets of subsamples. In these specifications, we regress our main dependent variable of interest on the main explanatory variable (ETC), a set of control variables, individual fixed effects, and time dummies. Results from FE regressions on the full sample indicate that ETC has a positive and significant impact on employment on average, in line with the results from Lachenmaier and Rottmann (2011) and Yang and Lin (2008).

Then, we disaggregate our sample iterating estimates with the same model as in specification (1), postulating that the effect of ETC is not linear across size and sectors. Therefore, in the high-tech (2) and low-tech (3) models, we take into account the level of technological intensity using the Pavitt classification (according to the OECD-Eurostat category of technological intensity), while in the firm-size specifications (4) and (5) we disaggregate the full sample according to the standard size classes of firms defined by Eurostat. When controlling for technological intensity, we find evidence of a non-linear relationship with positive and significant effects of ETC investments only for high-tech firms (defined as the sum of “high” and “medium-high” firms in the Pavitt taxonomy as opposed to the subsample of low-tech firms which encompasses Pavitt’s “medium-low” and “low” firms). On the other side, with respect to the size class, results show that the effect of ETC is positive and significant for both subsamples, although the impact is stronger in terms of magnitude for large firms. Finally, we also estimated specifications from (1) to (5) using Random Effect (RE) models.

Table 5
Fixed Effects (FE) 2008–2017: Interaction effect of ACAP, ETC gross of depreciation.

	(1)	(2)	(3)	(4)	(5)
	All	Hitech	Lowtech	SMEs	Large
ETC_{t-1} (ln)	0.009	0.027**	−0.005	0.009	0.037
	(0.008)	(0.011)	(0.012)	(0.009)	(0.030)
ACAP $Antecedents_{t-1}$	−0.013	0.004	−0.031*	−0.012	−0.034
	(0.010)	(0.012)	(0.016)	(0.011)	(0.081)
ETC_{t-1} (ln) * ACAP	0.003**	0.000	0.006**	0.003*	0.005
$Antecedents_{t-1}$	(0.002)	(0.002)	(0.002)	(0.002)	(0.008)
Constant	0.158	0.586***	−0.035	0.187	1.445**
	(0.155)	(0.195)	(0.224)	(0.157)	(0.722)
Observations	14,454	5721	8733	13,932	522
R-squared	0.560	0.555	0.574	0.546	0.684
Number of id	3392	1248	2144	3336	85
Time dummies	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses; Significance levels: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Hausman specification tests show that FE are more appropriate across all specifications.[8]

As far as the covariates are concerned (for the full table, with all controls, see Table 4A in the Appendix), value added positively impacts total employment at a firm level, confirming the pre-existing evidence, while profitability (ROI) does not seem to affect firm growth as measured with total employment. Somewhat counterintuitively, firm age does not play a role in determining firm growth as its coefficient is mostly insignificant across the different specification, while a supposed negative impact represents a widely acknowledged and consistent feature in the literature on industrial dynamics (Coad, 2007). However, the literature presents exceptions to this general feature and interestingly reveals that, in some cases, firm age can be positively correlated with firm growth in high-tech sectors, as in our relative subsample (Das, 1995). In addition, it can be noted that at the workers’ characteristics level, the median age and working experience of the firms’ workers, which are positively correlated with firm age, display a negative correlation with employment growth and may thus capture part of the negative impact of firm age on growth. Another interesting result is represented by the fact that average labour cost (measured as the total personnel costs on total employment) has a noisy effect on employment growth and a positive impact on SMEs and low-tech firms. Even if labour cost is generally negatively associated with firm performance, the relevant literature finds exceptions to this feature, especially when reference is made to SMEs, as it may reflect higher qualifications of the firms’ labour force (Lopez-Grazia and Puente, 2012). Finally, labour productivity negatively affects employment across all subsamples, confirming a stream of studies stating that productivity measures are poor predictors of growth and may be negatively correlated with it (Disney et al., 2003; Bottazzi et al., 2010).

In the second set of estimates, we extend the model assuming that the effects of process innovation on employment also depend on the level of dynamic capability of firms, besides the values of technological level and size class. Hence, we let ETC interact with our measure of antecedents of ACAP to disentangle the mechanism driving this relationship, thus explaining part of the complexity deriving from the heterogeneity between groups as well as within groups.

Estimates in Table 5 reveal that the interaction effect exists and is consistent with our hypothesis. In the full sample (column 1), the effect of ETC changes depending on the values of the ACAP of firms, with the interaction term displaying a positive and significant coefficient and the

[8] Estimates from RE models and the Hausman tests are available on request and omitted in the paper for the sake of brevity and clarity.

relative impact of ETC that loses significance. This result suggests that potential ACAP, as proxied by ACAP antecedents, conditions the ETC impact on employment growth rather than moderating it. As far as the subsamples are concerned, the coefficient associated with the interaction effect for the high-tech firms is not significant, while the coefficient for ETC remains essentially unvaried in terms of magnitude and significance (from 0.003 to 0.006). This result indicates that the potential ACAP does not contribute to explain the labour-friendly nature of process innovation for firms operating in sectors with medium-high and high-intensity of technology. One might interpret this result as suggesting that, in general, regardless of the absorptive capacity, firms operating in these sectors benefit more from investments in process innovation, as they take more advantage of compensation mechanisms effects (increase in jobs via income effects, new markets, enhanced productivity and higher competitiveness). In addition, this subsample could display low levels of heterogeneity among firms, as most organizations operating in high-tech and middle/high-tech sectors display high ACAP potential, as seen before.

However, for the remaining subsamples with the exception of large firms, the ACAP levels contribute to explain the employment variation generated by ETC with positive and significant coefficients associated with the interaction terms that do not vary much in terms of magnitude compared to the full sample. The significant and positive interaction coefficients for SMEs and low-tech firms confirm the idea that ACAP plays a pivotal role for middle-low and low-tech firms to make productive use of technological development that is usually generated in the "upstream" sectors (Cohen & Levinthal, 1989; 1990; Von Tunzelmann and Acha, 2005).[9] On the other hand, the coefficient associated with the interaction term is insignificant when considering the subsample of large firms (250+ employees). This evidence may suggest that larger firms, just like high-tech ones, do benefit from investments in ETC regardless of their relative level of ACAP. Still, the coefficient associated with ETC becomes insignificant when moving from the baseline to our augmented model that includes ACAP. All in all, this counterintuitive result may be due to the remarkably small subsample size (only 522 observations spread over 10 years).

Finally, we re-estimated specifications using Random Effect (RE) estimators, while Hausman specification tests indicate that FE are more appropriate for all specifications.[10]

Regarding the covariates (for the full table, with all controls, see Table 5A in the Appendix), similar remarks may be carried out compared to what emerged from the previous set of estimates. Value added confirms the positive impact on employment growth, while the role played by profitability (ROI), firm age, and labour cost is uncertain or ambivalent. Labour productivity is again negatively correlated with employment growth at a firm level, confirming the insights that emerged in the literature (Disney et al., 2003; Bottazzi et al., 2010).

To conclude, ETC generally positively impacts employment when combined with higher degrees of potential in absorptive capacity (ACAP). On the other hand, the conditional role of ACAP explains the heterogeneity among similar firms in size and industry: while high-tech firms usually do not show an even degree of heterogeneity and seem to benefit positively from process innovation, regardless of possible heterogeneity in ACAP. Similar evidence, albeit noisier, emerges also for large firms (250+ employees).

[9] However, the positive effect of the interaction term is offset by the negative effects of ACAP with respect to Low-Tech firms, which becomes weakly significant in this specification. This result is probably due to the fact that developing such capacities is relatively more expensive and less profitable in these sectors.

[10] Estimates from RE models and the relative Hausman tests are available on request and omitted in the paper for the sake of brevity and clarity.

6. Robustness check

In this section we present a series of robustness check to validate our measure for ETC and to mitigate further endogeneity concern that are not possibly addressed by the panel FE within estimator, i.e., time-varying heterogeneity. First, our proxy for ETC does not distinguish between the quality of the purchased industrial plants, machinery and equipment. This limitation could introduce a potential measurement error, which might explain the inter-sectoral differences observed in our baseline model. Sectors with higher technological intensity might have higher actual levels of innovative fixed capital assets, thus posing a threat to our interpretation of the moderating role of ACAP. To partially address this issue, we build an alternative measure of ETC that takes into account assets' depreciation, following the idea that relatively recent vintages of capital usually embody newer and more efficient technology thus exhibiting lower depreciation rates as compared to older vintages of capital assets (Sakellaris and Wilson, 2004). In this context, the robustness check serves as a sensitivity analysis, assessing the robustness of the estimates by varying the initial depreciation rate, set to 0 in the baseline model. To implement this, we retrieve total depreciation from the balance sheet and subtract it from ETC, weighting depreciation by the share of industrial plants, machinery and equipment over total tangible assets. Notably, the new proxy measure, accounting for depreciation, is expected to be positively correlated with actual ETC since newer vintages of capital will yield larger values for the proxy. Specifically, the proxy equals the stock of baseline measure, from which we subtract a component (depreciation) that is smaller for newer vintages of capital. Tables 6 and 7 show estimates from this robustness check, confirming baseline results: ETC has a positive effect on employment growth across the board, except for Low Tech firms, while ACAP moderate this positive effect, especially for SMEs.

In addition, to assess the robustness of our proxy measure, we conduct iterations using an alternative definition of ETC based on Community Innovation Survey (CIS) data. The rationale behind this test is to validate the construct of our measurement by evaluating its alignment with other measures 'consistent with theoretically derived hypotheses concerning the concepts that are being measured' (Elias and Purcell, 2004, p. 8; see also Adcock and Collier, 2001; Cattani et al., 2018). We retrieve information on expenditures related to 'Acquisition of machinery, equipment, and software (RMACX) — excluding expenditures on equipment for R&D—' from Section 5.2 of the questionnaire of the 2010 CIS survey. Subsequently, we calculate the ratio of expenditures on innovative machinery over total turnover for each NACE 2-digit sector [footnote omitted in the rebuttal letter]. Further, we discriminate between SMEs and large firms, obtaining two separate ratios for each sector. These ratios are applied as off-the-shelf indexes by multiplying them with the relative total turnover for each firm in our dataset. Table 8 reports the results of this robustness check, showing reassuringly similar signs, significance levels, and magnitudes compared

Table 6
Fixed Effects (FE), ETC net of depreciation - 2008–2017.

	(1)	(2)	(3)	(4)	(5)
	All	Hitech	Lowtech	SMEs	Large
ETC_{t-1} (ln)	0.011***	0.016***	0.004	0.010**	0.043**
	(0.004)	(0.005)	(0.006)	(0.004)	(0.017)
Constant	0.159	0.561***	−0.066	0.174	1.872***
	(0.140)	(0.166)	(0.206)	(0.138)	(0.622)
Observations	17,578	7240	10,338	16,887	691
R-squared	0.570	0.572	0.577	0.557	0.583
Number of id	3972	1516	2456	3900	114
Time dummies	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses; Significance levels: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table 7
Fixed Effects (FE) 2008–2017: Interaction effect of ACAP, ETC net of depreciation.

	(1)	(2)	(3)	(4)	(5)
	All	Hitech	Lowtech	SMEs	Large
ETC_{t-1} (ln)	0.005	0.019**	−0.006	0.005	0.024
	(0.007)	(0.008)	(0.010)	(0.007)	(0.028)
ACAP $Antecedents_{t-1}$	−0.011	0.006	−0.025*	−0.010	−0.041
	(0.009)	(0.011)	(0.014)	(0.009)	(0.073)
ETC_{t-1} (ln) * ACAP $Antecedents_{t-1}$	0.003**	0.000	0.005**	0.003*	0.006
	(0.001)	(0.002)	(0.002)	(0.002)	(0.008)
Constant	0.155	0.588***	−0.044	0.183	1.521**
	(0.154)	(0.194)	(0.224)	(0.156)	(0.731)
Observations	14,454	5721	8733	13,932	522
R-squared	0.560	0.554	0.574	0.545	0.682
Number of id	3392	1248	2144	3336	85
Time dummies	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses; Significance levels: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table 8
Fixed Effects & GMM 2008–2017: Alternative ETC measure based on CIS data.

	(1)	(2)	(3)	(4)
	FE	SYS-GMM	FE	SYS-GMM
ETC_{t-1} (ln)	0.024**	0.262**	0.015	0.039
	(0.011)	(0.121)	(0.013)	(0.042)
ACAP $Antecedents_{t-1}$			−0.005	0.009
			(0.007)	(0.030)
ETC_{t-1} (ln) * ACAP $Antecedents_{t-1}$			0.003*	0.004
			(0.002)	(0.006)
Constant	0.281*	−0.727	0.263	0.472
	(0.149)	(0.963)	(0.166)	(0.293)
Observations	17,578	17,573	14,454	14,454
R-squared	0.569		0.559	
Number of id	3972	3972	3392	3392
Time dummies	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Hansen J (*p*-value)		0.840		0.151
AR1 (p-value)		0.000		0.000
AR2 (p-value)		0.001		0.000

Notes: Standard errors in parentheses; Significance levels: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

to the baseline. Columns (1) and (3) present results from FE models without and with interaction terms with ACAP, respectively, while columns (2) and (4) report results obtained with dynamic SYS-GMM.[11] The only exception is represented by the coefficient associated with the interaction term with ACAP in specification (4), which turns out to be insignificant.

Finally, the potential persistence of the dependent variable over time raises concerns about our identification strategy, since current employment levels are likely influenced by past values at the firm level. To address this and correct for potential endogeneity arising from persistence and time-varying unobserved heterogeneity, we implement a dynamic partial adjustment model, which involves including the dependent variable with a one-year lag in the specification. Columns (1) and (3) in Table 9 show estimates obtained from this exercise, both without and with interactions with ACAP, respectively. These results align with those of the baseline model. However, introducing the lagged dependent variable among the regressors may raise additional endogeneity concerns due to possible correlation between individual fixed effects and the lagged dependent variable. To address this, we turn to SYS-GMM estimations, which involve two sets of equations. The first-difference equation addresses the endogeneity of the lagged dependent variable by taking first differences, thereby eliminating fixed effects. The level equation, on the other hand, uses lagged differences as instruments capturing the long-term relationships and dynamics in the data. SYS-GMM is chosen as our data may reasonably meet most of its constituent assumptions: i) current levels of the dependent variable are influenced by its prior values, ii) some regressors (i.e., ETC) may be endogenous and iii) individual fixed effects need to be taken into account. Conversely, we acknowledge that it may not be the most consistent and efficient estimator, given the additional assumptions that may not hold in our analysis. Some firms in our sample, particularly newly established ones, may exhibit values associated with our regressors that are still far from long-run means. Additionally, although the period of interest may be short enough to implement SYS-GMM, it may not be short enough to prevent instrument proliferation. In fact, the magnitude of the impact of ETC on employment, as estimated with GMM, turns out to be twice as large than that estimated with standard FE. As a robustness check, SYS-GMM estimates are presented in Columns (2) and (4) of Table 9, alongside estimates obtained with the within-FE estimator displayed in Tables 4 and 5, which remain our baseline of choice. Following Roodman (2009), we first-difference regressors suspected to be endogenous (lagged employment, ETC, ACAP, interaction term between ETC and ACAP), along with not strictly exogenous instruments that enter the model as predetermined (i.e., labour productivity and value-added). Other exogenous instruments, such as time trends, are also included. Consistent with Roodman's approach, we adopt only one lag of the endogenous variables unless AR tests suggest otherwise, in which case we adopt two lags. Estimates from this additional robustness check confirm our results.

7. Conclusions

This study exploits novel regional administrative labour market data to investigate the relationship between innovation and employment. We verify the impact of embodied technological change (ETC) on employment variations for a large sample of Italian manufacturing firms in the Emilia Romagna region. As we showed in our literature review, the existing research on the impact of ETC on employment is scarce, and the results show contrasting evidence depending on the analysed country, industry, firm size, and age. In such instances, there is room for investigating the possible presence of moderators or conditional variables

Table 9
Dynamic models: ETC net of depreciation - 2008–2017.

	(1)	(2)	(3)	(4)
	FE-DPAM	SYS-GMM	FE-DPAM	SYS-GMM
ETC_{t-1} (ln)	0.016***	0.039***	0.009	−0.016
	(0.005)	(0.013)	(0.008)	(0.015)
ACAP $Antecedents_{t-1}$			−0.013	−0.020
			(0.010)	(0.032)
ETC_{t-1} (ln) * ACAP $Antecedents_{t-1}$			0.003**	0.008*
			(0.002)	(0.005)
Constant	0.157	0.284**	0.158	0.382
	(0.140)	(0.138)	(0.155)	(0.270)
Observations	17,578	17,578	14,454	14,454
R-squared	0.570		0.560	
Number of id	3972	3972	3392	3392
Time dummies	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Hansen J (p-value)		0.117		0.065
AR1 (p-value)		0.000		0.000
AR2 (p-value)		0.000		0.000

Notes: Standard errors in parentheses; Significance levels: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

[11] For a discussion of the application and assumption of SYS-GMM, see comments to Table 8.

creating heterogeneity in the sign and the size of the potential effects. Therefore, we contribute to the literature by deepening the role of the absorptive capacity of firms, exploring "the level of prior related knowledge and diversity of background" of the observations composing our sample (Cohen and Levinthal, 1990). Besides, we also deepen the understanding of the impact of different organizational contingencies by disentangling the effects of ETC on employment under various conditions of technological intensity and firm size.

Taking advantage of a panel dataset spanning the period 2008–2017, we address endogeneity issues controlling for both time-varying and time-invariant unobservable factors and confounders. Our estimates, along with several tests as part of a robustness check, provide evidence of a positive and significant effect of ETC on employment variations. However, the impact is differentiated when investigating subsamples. Controlling for technological intensity, we find positive effects only for high-tech firms, while the disaggregation according to the size class displays positive effects relatively higher for large firms, suggesting that the limited absorptive capacity of SMEs may hinder this process. More interestingly, ETC's impact on employment is significant and positive across all sectors and sizes, only when interacting with firms' absorptive capacity. However, this positive effect is offset by costs associated with developing ACAP for Low Tech firms and is noisy for larger firms (250+ employees). ACAP, which is supposed to enhance the ability of firms to combine external and internal knowledge, is crucial in explaining the impact of process innovation on employment variations. This evidence supports the idea that absorptive capacity conditions the impact of innovative investments on firm growth. It follows and further develops the hypothesis that absorptive capacity mediates the relationship between external knowledge inflows (such as embodied technological change) and innovativeness, as Moilanen et al. (2014) pointed out.

We do acknowledge that our evidence is limited to the manufacturing industry of a specific regional context. Despite the appreciable level of firms' heterogeneity in our sample, this could raise issues about the generalizability of the results, as innovation is an uncertain process whose outcome depends, among many other factors, on the socio-economic and institutional context in which it takes place. Further research is thus needed to investigate if this evidence holds in different territorial contexts.

To conclude, these results bring about relevant managerial and policy implications, especially regarding regional innovation policies and labour market reforms. On the one hand, managers should acknowledge that the positive occupational impact of ETC is supported by managerial practices that strengthen external knowledge search strategies and firms' cooperative behaviours and favour human capital accumulation, thus paving the way for improved production quality. On the other hand, such practices can be effectively supported also at the policy level by enhancing cooperation between firms and between firms and research centres (both public and private), thus leveraging innovation policies' behavioural additionality. In addition, fostering long-term employment relationships is necessary, as they cultivate an environment where firms are incentivized and able to invest in activities that support their absorptive capacity, such as specific training programs. These sustained employment connections not only benefit the stability and cohesion within firms but also create fertile ground for developing skills and knowledge that are crucial for adaptation and growth.

For managers, it is imperative to recognize the complementarity between investments in technology, the pursuit of external knowledge, and the development of human capital. Simply investing up-to-date machinery and tools is insufficient without a corresponding long-term human resources strategy and a proactive approach to acquiring external knowledge. Merely replacing outdated machinery through replacement investment (*scrapping*) may not yield labour-friendly outcomes or result in significant labour-saving efficiencies, as suggested by Dosi et al. (2019).

On the contrary, investing in human capital and fostering the capabilities of the workforce may incur short-term costs but ultimately foster the creation of competitive advantages. Therefore, it should be embraced as the primary strategy for growth-oriented firms. By prioritizing investments in employees' skills and knowledge, firms can position themselves favourably in dynamic market environments, driving innovation, and resulting in an overall employment growth.

CRediT authorship contribution statement

Luca Cattani: Conceptualization, Formal analysis, Writing – original draft, Writing – review & editing, Methodology. **Francesco Savoia:** Conceptualization, Formal analysis, Methodology, Writing – original draft, Writing – review & editing. **Ludovico Bullini Orlandi:** Writing – original draft, Writing – review & editing.

Declaration of competing interest

None.

Data availability

The authors do not have permission to share data.

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Appendix A

Table 1A
List of variables.

Variables	Source	Type	Description
Total employment	SILER	Dependent variable	Number of employees expressed as annual labour unit "ULA" and measured as full time equivalent.*
VA	Aida BvD	Control	Valued added measured in thousands (euro), standardized by year

(*continued on next page*)

Table 1A (*continued*)

Variables	Source	Type	Description
Labour Cost	Aida BvD	Control	Cost per employee (expressed as number of employees) measured in thousands (euro).
Labour productivity	Aida BvD	Control	Value added (thousands of euro) over number of employees ratio
Immaterial Assets share	Aida BvD	Control	Immaterial assets on total assets (ratio)
Capital intensity	Aida BvD	Control	Capital intensity, total assets (thousands of euro) on total labour costs (thousands of euro).
ETC	Aida BvD	Main explanatory variable	Expenditure on industrial plants, machinery and equipment (thousands of euro).
VA over sales ratio	Aida BvD	Control	Value added over sales ratio (thousands euro).
ROI	Aida BvD	Control	Return on investments, measured as the ratio between the difference (value added – labour costs) over total sales
Firm age		Control	Firm age measured as number of years since its inception.
Workers' median age	SILER	Control	Workers' median age in firm I (expressed in years)
Workers' median working experience	SILER	Control	Workers' median working experience in firm I (expressed in years)
ACAP Antecedents	SILER	Main explanatory variable	Composite 1 to 7 points scale measuring the number of ACAP antecedents deployed by firm i at time t (discussed in Section 3).
Outsourcing (d)	Aida BvD	Item in ACAP scale	Expenditure in external services over total costs of production ratio (thousands of euro). The variable is operationalized as a dummy that equals 1 if this share in firm i exceeds the share over the full sample.
Exports (d)	Aida BvD	Item in ACAP scale	Dummy variable that equals 1 if the firm is licensed to export, 0 otherwise.
% Tenured > Median t-1 (d)	SILER	Item in ACAP scale	Dummy variable that equals 1 if the share of tenured workers over the firm's total employment exceeds the same ratio in the total sample and 0 otherwise.
% Graduates > Median t-1 (d)	SILER	Item in ACAP scale	Dummy variable that equals 1 if the share of graduate workers over the firm's total employment exceeds the same ratio in the total sample and 0 otherwise.
R&D (d)	SILER	Item in ACAP scale	Dummy variable that equals 1 if the firm's expenditures in R&D activities are positive and higher than zero, 0 otherwise
Network (d)	SILER	Item in ACAP scale	Dummy variable that equals 1 if the firm participates in the research network "Rete Alta Tecnologia" of the Emilia-Romagna region.
VA over sales ratio (d)	Aida BvD	Item in ACAP scale	Dummy variable that equals 1 if the VA over sales ratio in firm i is higher than the same ratio over the full sample.

Notes: * as defined by the Italian National Institute of Statistics (ISTAT).

Table 2A
Correlation matrix.

Id	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Total employment	1													
2	ETC (ln)	0.7363*	1												
3	Breadth	0.2516*	0.2092*	1											
4	VA (std)	0.9062*	0.7629*	0.2399*	1										
5	Labour productivity (ln)	0.1243*	0.3146*	0.0585*	0.5321*	1									
6	Labour cost (ln)	0.2155*	0.3273*	0.1453*	0.4967*	0.7340*	1								
7	VA over sales ratio	0.0369*	−0.0521*	0.3380*	0.0508*	0.0453*	0.0097	1							
8	Immaterial assets share	−0.0217*	−0.0355*	0.1256*	−0.0440*	−0.0599*	−0.0177	0.0126	1						
9	Firm age	0.1787*	0.1230*	0.0698*	0.2054*	0.1243*	0.1589*	−0.0183	−0.2702*	1					
10	ROI	0.0078	0.0456*	0.0628*	0.1428*	0.3195*	0.0273*	0.2920*	−0.0428*	0.0165	1				
11	Capital intensity	−0.0184	−0.0046	−0.0042	−0.0115	0.0098	−0.1382*	0.014	−0.0053	−0.0101	0.0279*	1			
12	Workers' median age	0.0193	−0.0383*	0.0856*	0.0274*	0.0256*	0.1343*	−0.0408*	−0.0353*	0.1401*	−0.0433*	−0.0027	1		
13	Workers' median working experience	−0.0501*	−0.1004*	0.1311*	−0.0344*	0.0196*	0.1225*	0.0411*	−0.1154*	0.3471*	−0.0243*	0.0003	0.4099*	1	
14	% Tenured > Median t-1 (d)	−0.1379*	−0.1440*	0.3885*	−0.1381*	−0.0479*	0.0244*	0.0434*	−0.0049	0.0462*	−0.0433*	0.0078	0.2069*	0.1337*	1

Notes: variables expressed in natural logarithm except for annual active labour unit (ULA).
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3A
Evolution over time of total employment.

Year	Full sample	High-potential	Others	Low-potential
2008	107,890.3	35,359.77	61,278.51	11,252.03
2009	110,861.9	36,590.3	62,094.40	12,177.21
2010	113,731.2	37,085	63,229.93	13,416.32
2011	115,813.4	37,981.27	64,884.62	12,947.48
2012	118,176.3	37,542.91	67,222.87	13,410.5
2013	119,952.2	38,517.95	71,050.02	10,384.24
2014	137,769.7	39,660.27	82,822.29	15,287.1
2015	134,504	38,799.17	81,433.12	14,271.69
2016	139,440.1	38,921.64	85,088.41	15,430.01
2017	1,098,139	340,458.3	639,104.20	118,576.6
Total	107,890.3	35,359.77	61,278.51	11,252.03

Notes: "Low potential", "Others" and "High potential" defined as firms endowed with 0–1 antecedents, 2–3 antecedents and 4–7 antecedents, respectively.

Table 4A
Fixed Effect, ETC gross of depreciation (2008–2017); full table with controls.

	(1)	(2)	(3)	(4)	(5)
	All	Hitech	Lowtech	SMEs	Large
ETC_{t-1} (ln)	0.016***	0.025***	0.007	0.015**	0.054***
	(0.005)	(0.007)	(0.009)	(0.006)	(0.020)
VA_{t-1} (ln)	0.707***	0.689***	0.725***	0.698***	0.544***
	(0.021)	(0.028)	(0.033)	(0.024)	(0.073)
Labour $prod._{t-1}$ (ln)	−0.641***	−0.610***	−0.671***	−0.632***	−0.570***
	(0.022)	(0.036)	(0.037)	(0.026)	(0.087)
Labour $cost_{t-1}$ (ln)	0.102***	−0.022	0.185***	0.102***	0.103
	(0.031)	(0.040)	(0.043)	(0.032)	(0.089)
VA over sales $ratio_{t-1}$ (ln)	−0.048***	−0.061***	−0.042**	−0.045***	0.010
	(0.013)	(0.019)	(0.019)	(0.013)	(0.069)
Imm. Assets $Share_{t-1}$ (ln)	−0.006	0.010	−0.021	−0.006	−0.019
	(0.016)	(0.022)	(0.024)	(0.017)	(0.054)
Firm age_{t-1} (ln)	0.010	0.045***	−0.017	0.010	0.034
	(0.013)	(0.015)	(0.019)	(0.013)	(0.034)
ROI_{t-1}	0.006	−0.003	0.030	0.005	0.149
	(0.013)	(0.018)	(0.047)	(0.013)	(0.214)
Capital $intensity_{t-1}$ (ln)	0.004*	0.001	0.006	0.004	0.003*
	(0.002)	(0.001)	(0.005)	(0.004)	(0.001)
Workers' median age	−0.007***	−0.005**	−0.009***	−0.007***	−0.022***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.007)
Median working exp.	−0.020***	−0.021***	−0.019***	−0.019***	−0.017***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.006)
Median working exp.2	0.001***	0.001***	0.001**	0.001***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
% Tenured > Median (d)	−0.044***	−0.046***	−0.043***	−0.045***	−0.017
	(0.004)	(0.006)	(0.006)	(0.004)	(0.012)
Constant	0.157	0.555***	−0.066	0.173	1.846***
	(0.140)	(0.167)	(0.207)	(0.139)	(0.618)
Observations	17,578	7240	10,338	16,887	691
R-squared	0.570	0.573	0.577	0.558	0.585
Number of id	3972	1516	2456	3900	114
Time dummies	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses. Significance levels: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table 5A
Fixed Effects (FE) 2008–2017: Interaction effect of ACAP, ETC gross of depreciation; full table with controls.

	(1)	(2)	(3)	(4)	(5)
	All	Hitech	Lowtech	SMEs	Large
ETC_{t-1} (ln)	0.009	0.027**	−0.005	0.009	0.037
	(0.008)	(0.011)	(0.012)	(0.009)	(0.030)
ACAP $Antecedents_{t-1}$	−0.013	0.004	−0.031*	−0.012	−0.034
	(0.010)	(0.012)	(0.016)	(0.011)	(0.081)
ETC_{t-1} (ln) * ACAP $Antecedents_{t-1}$	0.003**	0.000	0.006**	0.003*	0.005
	(0.002)	(0.002)	(0.002)	(0.002)	(0.008)
VA_{t-1} (ln)	0.696***	0.667***	0.719***	0.687***	0.580***
	(0.026)	(0.032)	(0.038)	(0.027)	(0.082)
Labour $prod._{t-1}$ (ln)	−0.627***	−0.592***	−0.655***	−0.619***	−0.544***
	(0.029)	(0.041)	(0.043)	(0.030)	(0.087)
Labour $cost_{t-1}$ (ln)	0.105***	−0.021	0.176***	0.103***	0.084
	(0.036)	(0.044)	(0.049)	(0.037)	(0.090)
VA over sales $ratio_{t-1}$ (ln)	−0.052***	−0.071***	−0.047**	−0.048***	−0.056
	(0.014)	(0.021)	(0.019)	(0.015)	(0.058)
Imm. Assets $Share_{t-1}$ (ln)	−0.006	0.008	−0.020	−0.005	−0.043
	(0.019)	(0.027)	(0.027)	(0.019)	(0.074)
Firm age_{t-1} (ln)	0.016	0.048***	−0.011	0.015	0.033
	(0.014)	(0.016)	(0.020)	(0.014)	(0.046)
ROI_{t-1}	0.000	0.004	0.010	−0.000	0.008
	(0.013)	(0.019)	(0.033)	(0.013)	(0.186)
Capital $intensity_{t-1}$ (ln)	0.004	−0.003*	0.007	0.004	0.004
	(0.004)	(0.002)	(0.005)	(0.005)	(0.003)
Workers' median age	−0.007***	−0.004*	−0.008***	−0.006***	−0.027***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.008)
Median working exp.	−0.022***	−0.022***	−0.021***	−0.022***	−0.017***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.006)
Median working exp.2	0.001***	0.001***	0.001***	0.001***	0.002

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Table 5A (*continued*)

	(1) All	(2) Hitech	(3) Lowtech	(4) SMEs	(5) Large
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
% Tenured > Median (d)	−0.047***	−0.047***	−0.047***	−0.048***	−0.027**
	(0.005)	(0.007)	(0.007)	(0.005)	(0.012)
Constant	0.158	0.586***	−0.035	0.187	1.445**
	(0.155)	(0.195)	(0.224)	(0.157)	(0.722)
Observations	14,454	5721	8733	13,932	522
R-squared	0.560	0.555	0.574	0.546	0.684
Number of id	3392	1248	2144	3336	85
Time dummies	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses. Significance levels: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table 6A
Fixed Effects (FE), ETC net of depreciation - 2008–2017; full table with controls.

	(1) All	(2) Hitech	(3) Lowtech	(4) SMEs	(5) Large
ETC_{t-1} (ln)	0.011***	0.016***	0.004	0.010**	0.043**
	(0.004)	(0.005)	(0.006)	(0.004)	(0.017)
VA_{t-1} (ln)	0.712***	0.698***	0.728***	0.703***	0.555***
	(0.021)	(0.026)	(0.032)	(0.023)	(0.073)
Labour $prod._{t-1}$ (ln)	−0.644***	−0.618***	−0.673***	−0.636***	−0.583***
	(0.022)	(0.036)	(0.037)	(0.025)	(0.087)
Labour $cost_{t-1}$ (ln)	0.104***	−0.019	0.186***	0.104***	0.113
	(0.031)	(0.040)	(0.043)	(0.032)	(0.089)
VA over sales $ratio_{t-1}$ (ln)	−0.049***	−0.062***	−0.043**	−0.046***	0.013
	(0.013)	(0.019)	(0.019)	(0.013)	(0.071)
Imm. Assets $Share_{t-1}$ (ln)	−0.010	0.002	−0.023	−0.010	−0.022
	(0.016)	(0.021)	(0.024)	(0.016)	(0.054)
Firm age_{t-1} (ln)	0.010	0.043***	−0.017	0.010	0.029
	(0.013)	(0.015)	(0.019)	(0.013)	(0.034)
ROI_{t-1}	0.005	−0.004	0.030	0.005	0.154
	(0.012)	(0.018)	(0.047)	(0.012)	(0.211)
Capital $intensity_{t-1}$ (ln)	0.004*	0.001	0.006	0.004	0.002*
	(0.002)	(0.001)	(0.005)	(0.004)	(0.001)
Workers' median age	−0.007***	−0.005**	−0.009***	−0.007***	−0.022***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.007)
Median working exp.	−0.020***	−0.021***	−0.019***	−0.020***	−0.017***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.006)
Median working exp.2	0.001***	0.001***	0.001**	0.001***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
% Tenured > Median (d)	−0.044***	−0.046***	−0.043***	−0.045***	−0.016
	(0.004)	(0.006)	(0.006)	(0.004)	(0.012)
Constant	0.159	0.561***	−0.066	0.174	1.872***
	(0.140)	(0.166)	(0.206)	(0.138)	(0.622)
Observations	17,578	7240	10,338	16,887	691
R-squared	0.570	0.572	0.577	0.557	0.583
Number of id	3972	1516	2456	3900	114
Time dummies	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES

Notes: Standard errors in parentheses. Significance levels: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table 7A
FE 2008–2017: Interaction effect of ACAP, ETC net of depreciation; full table with controls.

	(1) All	(2) Hitech	(3) Lowtech	(4) SMEs	(5) Large
ETC_{t-1} (ln)	0.005	0.019**	−0.006	0.005	0.024
	(0.007)	(0.008)	(0.010)	(0.007)	(0.028)
ACAP $Antecedents_{t-1}$	−0.011	0.006	−0.025*	−0.010	−0.041
	(0.009)	(0.011)	(0.014)	(0.009)	(0.073)
ETC_{t-1} (ln) * ACAP $Antecedents_{t-1}$	0.003**	0.000	0.005**	0.003*	0.006
	(0.001)	(0.002)	(0.002)	(0.002)	(0.008)
VA_{t-1} (ln)	0.701***	0.676***	0.721***	0.691***	0.591***
	(0.026)	(0.030)	(0.037)	(0.026)	(0.083)
Labour $prod._{t-1}$ (ln)	−0.630***	−0.599***	−0.656***	−0.622***	−0.557***
	(0.028)	(0.040)	(0.042)	(0.029)	(0.086)

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Table 7A (*continued*)

	(1) All	(2) Hitech	(3) Lowtech	(4) SMEs	(5) Large
Labour cost$_{t-1}$ (ln)	0.107***	−0.017	0.177***	0.105***	0.093
	(0.036)	(0.045)	(0.049)	(0.037)	(0.089)
VA over sales ratio$_{t-1}$ (ln)	−0.053***	−0.071***	−0.047**	−0.049***	−0.052
	(0.014)	(0.021)	(0.019)	(0.015)	(0.060)
Imm. Assets Share$_{t-1}$ (ln)	−0.009	0.001	−0.022	−0.009	−0.037
	(0.018)	(0.026)	(0.027)	(0.019)	(0.075)
Firm age$_{t-1}$ (ln)	0.015	0.046***	−0.012	0.015	0.024
	(0.014)	(0.016)	(0.020)	(0.014)	(0.047)
ROI$_{t-1}$	−0.000	0.003	0.010	−0.001	0.012
	(0.012)	(0.018)	(0.033)	(0.012)	(0.182)
Capital intensity$_{t-1}$ (ln)	0.004	−0.003*	0.007	0.004	0.003
	(0.004)	(0.002)	(0.005)	(0.005)	(0.003)
Workers' median age	−0.007***	−0.004*	−0.008***	−0.006***	−0.028***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.008)
Median working exp.	−0.022***	−0.022***	−0.021***	−0.022***	−0.018***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.006)
Median working exp.2	0.001***	0.001***	0.001***	0.001***	0.002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
% Tenured > Median (d)	−0.047***	−0.046***	−0.047***	−0.048***	−0.025**
	(0.005)	(0.007)	(0.007)	(0.005)	(0.012)
Constant	0.155	0.588***	−0.044	0.183	1.521**
	(0.154)	(0.194)	(0.224)	(0.156)	(0.731)
Observations	14,454	5721	8733	13,932	522
R-squared	0.560	0.554	0.574	0.545	0.682
Number of id	3392	1248	2144	3336	85
Time dummies	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses. Significance levels: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table 8A
FE & GMM 2008–2017: Interaction effect of ACAP, alternative proxy of ETC (CIS data); full table of controls.

	(1) FE	(2) SYS-GMM	(3) FE	(4) SYS-GMM
ETC$_{t-1}$ (ln)	0.024**	0.262**	0.015	0.039
	(0.011)	(0.121)	(0.013)	(0.042)
ACAP Antecedents$_{t-1}$			−0.005	0.009
			(0.007)	(0.030)
ETC$_{t-1}$ (ln) * ACAP Antecedents$_{t-1}$			0.003*	0.004
			(0.002)	(0.006)
VA$_{t-1}$ (ln)	0.695***	0.651***	0.688***	0.901***
	(0.025)	(0.136)	(0.029)	(0.042)
Labour prod.$_{t-1}$ (ln)	−0.650***	−1.253***	−0.639***	−0.961***
	(0.021)	(0.091)	(0.027)	(0.053)
Labour cost$_{t-1}$ (ln)	0.111***	0.842***	0.114***	0.042
	(0.031)	(0.269)	(0.036)	(0.080)
VA over sales ratio$_{t-1}$ (ln)	−0.027*	0.167	−0.032*	0.101*
	(0.016)	(0.115)	(0.018)	(0.057)
Imm. Assets Share$_{t-1}$ (ln)	−0.016	0.288	−0.018	0.153
	(0.015)	(0.466)	(0.017)	(0.133)
Firm age$_{t-1}$ (ln)	0.008	0.068	0.013	−0.041*
	(0.013)	(0.081)	(0.014)	(0.025)
ROI$_{t-1}$	0.014	0.239	0.009	0.043
	(0.010)	(0.264)	(0.009)	(0.088)
Capital intensity$_{t-1}$ (ln)	0.004*	0.019	0.004	0.011
	(0.002)	(0.014)	(0.004)	(0.009)
Workers' median age	−0.007***	−0.050**	−0.007***	−0.001
	(0.001)	(0.021)	(0.001)	(0.007)
Median working exp.	−0.020***	−0.016	−0.022***	−0.005
	(0.002)	(0.021)	(0.002)	(0.009)
Median working exp.2	0.001***	0.010**	0.001***	0.003*
	(0.000)	(0.005)	(0.000)	(0.001)
% Tenured > Median (d)	−0.044***	−0.210	−0.047***	−0.184**
	(0.004)	(0.141)	(0.005)	(0.081)

(*continued on next page*)

Table 8A (*continued*)

	(1)	(2)	(3)	(4)
	FE	SYS-GMM	FE	SYS-GMM
Constant	0.281*	−0.727	0.263	0.472
	(0.149)	(0.963)	(0.166)	(0.293)
Observations	17,578	17,573	14,454	14,454
R-squared	0.569		0.559	
Number of id	3972	3972	3392	3392
Time dummies	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Hansen J (p-value)		0.840		0.151
AR1 (p-value)		0.000		0.000
AR2 (p-value)		0.001		0.000

Notes: Standard errors in parentheses. Significance levels: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table 9A
Dynamic models: ETC net of depreciation – 2008–2017.

	(1)	(2)	(3)	(4)
	FE	SYS-GMM	FE	SYS-GMM
ETC_{t-1} (ln)	0.016***	0.039***	0.009	−0.016
	(0.005)	(0.013)	(0.008)	(0.015)
ACAP $Antecedents_{t-1}$			−0.013	−0.020
			(0.010)	(0.032)
ETC_{t-1} (ln) * ACAP $Antecedents_{t-1}$			0.003**	0.008*
			(0.002)	(0.005)
L.l_EMPL	0.641***		0.627***	0.954***
	(0.022)		(0.029)	(0.021)
VA_{t-1} (ln)	0.066***	0.965***	0.069***	
	(0.012)	(0.021)	(0.013)	
Labour $prod._{t-1}$ (ln)	0.000	−0.965***	0.000	0.017
	(0.000)	(0.053)	(0.000)	(0.061)
Labour $cost_{t-1}$ (ln)	0.102***	−0.013	0.105***	−0.019
	(0.031)	(0.086)	(0.036)	(0.093)
VA over sales $ratio_{t-1}$ (ln)	−0.048***	0.056	−0.052***	0.110***
	(0.013)	(0.053)	(0.014)	(0.040)
Imm. Assets $Share_{t-1}$ (ln)	−0.006	0.025	−0.006	−0.042
	(0.016)	(0.185)	(0.019)	(0.026)
Firm age_{t-1} (ln)	0.010	−0.059**	0.016	−0.014
	(0.013)	(0.027)	(0.014)	(0.026)
ROI_{t-1}	0.006	−0.073	0.000	0.109
	(0.013)	(0.172)	(0.013)	(0.198)
Capital $intensity_{t-1}$ (ln)	0.004*	0.004	0.004	0.020***
	(0.002)	(0.008)	(0.004)	(0.006)
Workers' median age	−0.007***	0.001	−0.007***	−0.006
	(0.001)	(0.007)	(0.001)	(0.006)
Median working exp.	−0.020***	−0.013	−0.022***	−0.014*
	(0.002)	(0.009)	(0.002)	(0.008)
Median working exp.2	0.001***	0.002	0.001***	0.003**
	(0.000)	(0.002)	(0.000)	(0.001)
% Tenured > Median (d)	−0.044***	−0.180***	−0.047***	−0.114***
	(0.004)	(0.060)	(0.005)	(0.036)
Constant	0.157	0.284**	0.158	0.382
	(0.140)	(0.138)	(0.155)	(0.270)
Observations	17,578	17,578	14,454	14,454
R-squared	0.570		0.560	
Number of id	3972	3972	3392	3392
Time dummies	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Hansen J (p-value)		0.117		0.065
AR1 (p-value)		0.000		0.000
AR2 (p-value)		0.000		0.000

Notes: Standard errors in parentheses. Significance levels: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. After the inclusion of the lagged dependent variable in the model, Employment at time *t-1* and VA at time *t-1* were automatically alternatively omitted in specification (2) and (4), respectively, due to collinearity by Stata command *xtabond2*. Since the correlation coefficient between lagged Value added and lagged Employment is 0.90, to mitigate possible multicollinearity issues that may be further exacerbated by the instrumentation procedure (as the same variables were not dropped in the FE dynamic model), we repeated the estimates by either omitting or further lagging (*t-2*) Value added. Estimates from this exercise are displayed in Table 10A.

Table 10A
GMM: ETC net of depreciation; Value added included with 2-year lags – 2008–2017.

	(1)	(2)	(3)	(4)
	Lagged	Omitted	Lagged	Omitted
ETC_{t-1} (ln)	0.036**	0.039***	−0.034**	−0.016
	(0.015)	(0.013)	(0.017)	(0.015)
ACAP $Antecedents_{t-1}$			−0.031	−0.020
			(0.035)	(0.032)
ETC_{t-1} (ln) * ACAP $Antecedents_{t-1}$			0.009*	0.008*
			(0.005)	(0.005)
L.l_EMPL	0.994***	0.965***	0.960***	0.954***
	(0.021)	(0.021)	(0.033)	(0.021)
VA_{t-2} (ln)	−0.029***		−0.044***	
	(0.011)		(0.012)	
Labour $prod_{t-1}$ (ln)	0.029	−0.000	0.081***	0.017
	(0.059)	(0.051)	(0.017)	(0.061)
Labour $cost_{t-1}$ (ln)	−0.037	−0.013	0.203***	−0.019
	(0.097)	(0.086)	(0.040)	(0.093)
VA over sales $ratio_{t-1}$ (ln)	−0.026	0.056	−0.067***	0.110***
	(0.055)	(0.053)	(0.021)	(0.040)
Imm. Assets $Share_{t-1}$ (ln)	0.133	0.025	−0.055**	−0.042
	(0.227)	(0.185)	(0.026)	(0.026)
Firm age_{t-1} (ln)	−0.059	−0.059**	0.002	−0.014
	(0.037)	(0.027)	(0.015)	(0.026)
ROI_{t-1}	−0.064	−0.073	−0.022*	0.109
	(0.239)	(0.172)	(0.013)	(0.198)
Capital $intensity_{t-1}$ (ln)	0.007	0.004	0.018***	0.020***
	(0.010)	(0.008)	(0.005)	(0.006)
Workers' median age	−0.005	0.001	−0.009***	−0.006
	(0.009)	(0.007)	(0.002)	(0.006)
Median working exp.	0.007	−0.013	−0.022***	−0.014*
	(0.010)	(0.009)	(0.003)	(0.008)
Median working exp.2	0.002	0.002	0.001***	0.003**
	(0.002)	(0.002)	(0.000)	(0.001)
% Tenured > Median (d)	−0.269***	−0.180***	−0.045***	−0.114***
	(0.066)	(0.060)	(0.006)	(0.036)
Constant	0.297*	0.269*	−0.612***	0.382
	(0.164)	(0.137)	(0.189)	(0.270)
Observations	13,624	17,578	11,120	14,454
Number of id	2906	3972	2451	3392
Time dummies	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Hansen J (p-value)	0.341	0.117	0.006	0.065
AR1 (p-value)	0.000	0.000	0.000	0.000
AR2 (p-value)	0.000	0.000	0.001	0.000

Notes: Standard errors in parentheses. Significance levels: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

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