



The Impact of Digital Technologies on Self-Employment Dynamics in Italy

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Abstract

This paper examines the causal impact of the adoption of advanced automation and big data on the dynamics of self-employed workers in Italy between 2015 and 2019. Combining data on employment dynamics and on technology adoption at the level of provinces and macrosectors, the analysis shows that the two technologies exert different effects. Advanced automation has a negative impact on the shares of self-employed individuals, whereas the opposite is found for big data. In both cases, the effects are primarily driven by solo self-employed workers (i.e., self-employed individuals without employees). These results are consistent with theories predicting that big data fosters opportunity-based forms of entrepreneurship, whereas advanced automation is associated with a generalized worsening of working arrangements.

Keywords Self-employment · Digital technology · Big data · Advanced automation · Labour markets

JEL Classification J21 · J23 · J24 · M51 · O33

1 Introduction

The impact of new digital technologies on employment dynamics has been extensively investigated in the literature. However, few studies analyse technologies other than robotics and automation. The idea underpinning these empirical works is that the interaction between workers' characteristics (e.g., skills, knowledge, education), job-specific tasks and features of the technology jointly determine what occupations are more exposed and affected (Acemoglu and Restrepo 2020; Balsmeier and Woerter 2019; Bachmann et al. 2024; Caselli et al. 2025b, a; Consoli et al. 2023; Dengler and Matthes 2018; Engberg et al. 2025; Graetz and Michaels 2018; Montobbio et al. 2022).

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Certain technologies may substitute and displace workers in certain occupations or tasks, whereas others may complement and reinstate human activities, and even create new tasks and jobs. Given the exposure of each occupation to a technology and the characteristics of the workforce, thus, the intensity of technology adoption determines more or less significant changes in the level and composition of paid employment at the firm, industry and regional level.

In contrast, less attention has been paid to the empirical effects that digital technologies have on the dynamics of self-employment, despite the theoretically ambiguous connection between technological progress and entrepreneurship (Fossen and Sorgner 2021; Kim and Thompson 2025). A novel technology can reduce new entrepreneurial activities by competing for financial and human resources and by increasing start-up costs, but it can also drive more employed individuals into self-employment via two alternative channels. On the one hand, technology-displaced (or potentially displaced) workers may have the necessity to look for alternative forms of employment; on the other hand, the new technology may create business opportunities, facilitate access to information and networks, and reduce uncertainty, thereby facilitating entrepreneurial activities. In particular, digital technologies may influence the entry into entrepreneurship by affecting the employees' opportunity cost of self-employment.

The objective of this study is to investigate how the penetration of advanced automation and big data affected the dynamics of self-employment in Italy from 2015 to 2019. We analyse the information on the adoption rates of these technologies at the province (NUTS 3) and macrosector level between 2016 and 2018. Italy is an interesting case in point because of the diffusion of robots and big data (Bratta et al. 2023; Bronzini et al. 2025; Caselli et al. 2025a; Dottori 2021), but also because of the historically high share of self-employment in total employment (Boeri et al. 2020). To interpret our findings and understand the underlying mechanisms, we distinguish between self-employed people with employees and those without employees (also known as 'solo self-employed'); moreover, we distinguish the self-employed individuals without employees who have only one client from those with multiple clients. Finally, we estimate the effects on the dynamics of all employees and firms' collaborators, as these results help us to interpret and understand the overall impact of adopting these technologies.

We find evidence that advanced automation leads to fewer transitions because where advanced automation is more intense there are no significant changes in the share of self-employed with employees and the share of self-employed people without employees strongly decreases. Moreover, advanced automation is associated with an increased share of the most vulnerable group of workers, that is the self-employed individuals with only one client and the coordinated and continuous collaborators (hereafter, collaborators). Hence, advanced automation appears not to offer much opportunities to paid workers and self-employees and it may work, to borrow Fossen and Sorgner (2021)'s characterization, as a 'destructive' form of digitalization. Conversely, our analysis shows that big data is associated with higher shares of self-employed people, in particular solo self-employed people who entertain business relationships with multiple clients. It also reduces the share of firms' collaborators. These findings are in line with a view of big data as creating opportunities for both paid employees and less vulnerable self-employed individuals, and this makes it a 'transformative' form

of digitalization. The insignificant effects of big data on the share of self-employed individuals with employees, however, suggest that big data-related transitions to self-employment are associated with limited growth opportunities.

From the methodological viewpoint, the potential endogeneity of technology adoption is addressed with an instrumental variable (IV) approach, borrowing from Caselli et al. (2025a). As explained by Cohen and Levinthal (1990), technology diffusion depends both on the advancements at the technological frontier and on the absorptive capacity of the incumbent firms. Thus, we build each instrumental variable using an exogenous measure of the global technological frontier at the macrosector level and we interact this instrumental variable with a province-specific factor that influences the likelihood of appropriating such global knowledge and thus captures the variation in the local absorptive capacity.

Our work relates to different strands of the literature.

First, it refers and contributes to the literature focusing on the relationship between technological progress and self-employment dynamics. Previous studies showed that different forms of technological progress exert heterogeneous effects on different occupational groups. As reviewed in Sect. 2, the literature has produced contrasting results, and this strengthens the case for further empirical work. Previous works using household/workers surveys mainly considered individual transitions and differentiated workers' groups in terms of the potential (a priori) exposure of their occupations to labour substitution or augmentation (Bachmann et al. 2025; Fossen and Sorgner 2021, 2022; Kim et al. 2025; Zhang et al. 2022). The actual intensity of technology adoption, however, was not considered in these studies. Instead, we use aggregated data at the regional and sectoral level to exploit the information about the actual intensity of technology adoption and to examine how it correlates with self-employment dynamics across provinces and macrosectors.¹ Thus, differently from previous studies, while we do not differentiate the occupations in terms of their potential risk of displacement, we account for the actual diffusion of the technology. Moreover, we offer an assessment about the 'destructive' or 'transformative' nature of these two technologies on the basis of a rich set of empirical results regarding various subgroups of self-employed people, rather than on the basis of an a priori classification of exposed occupations.²

Second, our work indirectly contributes to the literature on the determinants of entrepreneurship and on business dynamics. Although entrepreneurship does not perfectly coincide (either at the theoretical or empirical level) with self-employment, the analysis of self-employment dynamics complements the recent studies focusing on the contribution of nonemployer businesses to overall business dynamics, net entry rates, firm competition and market structure (Bento and Restuccia 2025). Indeed, as business surveys do not typically include nonemployer businesses, the investigation of the evolution of solo self-employed individuals permits to draw a more complete picture of the overall business dynamics. Cui and Xu (2025), for instance, examine new registered enterprises data and industrial robot data in China, and conclude that robot adoption

¹ Also Kim and Thompson (2025) consider aggregate regional data about the growth of nonemployer businesses (i.e., solo self-employed individuals), but they do not include any measure of technology adoption. Rather, they use the lagged task-based composition of local labour markets to proxy for potential adoption.

² A possible extension of our work in this direction, data permitting, would be to diversify the workers in terms of their pre-transition characteristics, such as skills and abilities.

is negatively associated with regional entrepreneurial activities, although high-quality entrepreneurial activities tend to expand. Kim and Thompson (2025) find that local labour markets with a high share of routine task-intensive jobs and higher adoption of information technology exhibit a higher growth of nonemployer businesses through self-employment in nonroutine manual task-intensive jobs.

Finally, our analysis relates to the above-mentioned rich literature that investigates the impact of new digital technologies on employment dynamics across groups of occupations. Most studies have focused on the diversified effects of technology adoption on different occupational groups within adopting and non-adopting firms. As individuals may choose to move from paid employment to self-employment, and not only across occupations in paid positions, our analysis contributes in that it uncovers a potentially important part of the overall employment dynamics associated with the adoption of new digital technologies.

Besides contributing to the literature on the role that advanced automation and big data exert on self-employment dynamics, this work bears on policymaking and industrial relations. As pointed out by Cieřlik and van Stel (2024), policymakers' attention to the solo self-employed individuals has grown in recent years because they can be understood as a particularly vulnerable segment of the labour market. The Organisation for Economic Co-operation and Development (OECD), for instance, has tackled the challenges from classifying incorrectly the status of workers falling in the so-called grey-zone between the traditional dependent employment and own-account workers (e.g., solo self-employed workers), in particular in the cases of economic dependence of the worker on a single client (OECD 2019). Recognizing the potential boost to various types of self-employment that the new technologies may cause, in 2022 the European Commission adopted specific guidelines to allow for the possibility of collective agreements by solo self-employed people. While this decision addresses the reasonable concern that certain types of self-employed people may lose negotiating power vis-a-vis few large clients, the salience of this policy concern depends on how each technology affects the self-employment dynamics. Our findings show that different digital technologies exert very different effects, with advanced automation (but not big data) contributing to the expansion of vulnerable working arrangements.

The remainder of the article proceeds as follows. Section 2 clarifies the theoretical framework on which the literature on self-employment dynamics is based (i.e., the dichotomy between push/necessity vs pull/opportunity drivers) and discusses how we operationalize it in this work. Section 3.1 describes the dataset used to carry out the empirical analysis. Section 3.2 presents the empirical model and the instrumental variables approach adopted to address endogeneity concerns. Section 4 presents and discusses the results from the estimations. Section 5 offers a discussion of the limitations of this work as well as of its implications for policymakers and the society at large.

2 Theoretical Framework and Review of the Literature

Transitions into self-employment can be understood within a simple conceptual framework where each worker selects her occupational status (i.e., paid employment versus

self-employment) on the basis of her expected utility, given her entrepreneurial ability (Parker 2004). Given the characteristics of the person (Simoes et al. 2016), two opposing forces can affect her decision to choose self-employment: positive opportunity-related factors that ‘pull’ her into exploring new promising entrepreneurial activities, and negative factors that ‘push’ her into entrepreneurship for the lack of better alternatives in paid employment (Gilad and Levine 1986).

The introduction of a new technology is a contingency that might affect such choice about the preferred occupational status. Technological progress, in particular, can modify the opportunity cost of leaving a paid occupation for an entrepreneurial initiative. The theoretical relationship between digital technologies and transitions into self-employment and entrepreneurship is ambiguous as it is governed by two opposing mechanisms (Fossen and Sorgner 2021).

The first necessity-driven (or ‘push’) mechanism derives from the displacement that arises from either the substitution of tasks performed by the new technology (e.g., robots tend to substitute humans in various routine tasks) or through the obsolescence of certain knowledge and skills (e.g., big data analysis requires machine learning techniques diverse from mainstream statistical methods). As new technologies impose occupational risks and reduce the opportunity cost of self-employment, incumbent employees may be ‘pushed’ out of paid employment into self-employment. This ‘push’ effect would lead to a positive relationship between technology diffusion and transitions into self-employment. However, if the technology entails high fixed costs or requires specific competences to be adopted, paid workers may not be capable of starting their own business despite the necessity-driven motivation: this reduces the opportunity cost of remaining in paid employment and limits the extent of the ‘push’.³

The second opportunity-driven (or ‘pull’) mechanism revolves around the technology-induced creation of new products, tasks and business models that generate new entrepreneurial opportunities. The stronger this opportunity-driven motivation, the greater the number of employees hired when these new activities expand. The intensity of this second channel, however, varies according to whether the technology-driven productivity gains lead to higher wages for paid employees with necessary complementary skills: this would make paid employment relatively more attractive and the opportunity cost of self-employment higher. Hence, the intensity of the opportunity-driven (or ‘pull’) channel depends on the way in which the technology actually relates to the skills and productivity of paid employees.

Different empirical strategies have been used in the literature to operationalize the distinction between necessity-driven (or ‘push’) and opportunity-driven (or ‘pull’) transitions. Van der Zwan et al. (2016) use the business owners’ self-assessments about their opportunity-driven and necessity-driven motivations as solicited by the questions in the Eurobarometer survey. Fairlie and Fossen (2020) and Zhang et al. (2022), instead, consider the entrepreneur’s prior work status, with former paid employees labelled as opportunity entrepreneurs and former unemployed people labelled as necessity entrepreneurs. Fossen and Sorgner (2021) and Kim et al. (2025) capture heterogeneity

³ The literature has shown that small businesses and startups can meet financial and technical difficulties to keep up with breakthroughs and innovations (Bijmans and Konings 2020). When expensive and complex technologies provide a competitive wedge to their adopters, they might end up favouring larger incumbent companies and their employees over the new self-employed workers.

in entrepreneurial motivations by distinguishing between entrepreneurs with unincorporated and with incorporated businesses, as in Levine and Rubinstein (2017).⁴ Finally, to capture the self-employment motivations, Bachmann et al. (2025) distinguish between the self-employed people with employees and those without employees: the former are typically driven by ambition and higher levels of education (associated with opportunity-driven transitions), whereas solo self-employment often results from a lack of better employment options (associated with necessity-driven transitions). Also Boeri et al. (2020) maintain that self-employed people without employees have lower social insurance, wage and job protection than paid employees, and they often work less than what they would like to. Finally, Boeri et al. (2020), Böheim and Mühlberger (2009) and Muehlberger and Pasqua (2009) explain that solo self-employed people work with very little flexibility when they are highly dependent on a single client.⁵ Hence, we maintain that the distinction between solo self-employment with one client and with multiple clients can be used to distinguish the two transition types.

Given the structure of our data, we adopt the distinction among self-employed workers based on the presence of employees or lack thereof, and we also consider the numerosity of clients for the solo self-employed people. Each category of self-employment is expected to react differently to the push and pull forces moved by the new technologies, and we will exploit the distinction to assess the strength of the opportunity-driven and necessity-driven motivations.

It is worth noticing that all the forces at work can produce a variety of situations. A technology may end up with being a ‘destructive’ form of digitalization (borrowing the Fossen and Sorgner 2021’s label) if its pull and push forces are not strong enough to compensate, via more self-employment opportunities, its displacement effects on human activities. In this case, we expect that there is not a positive relationship between the intensity of technology adoption and the shares of both paid workers and of self-employed individuals. Moreover, we expect a negative impact on self-employed with employees and solo self-employed with multiple clients. A ‘destructive’ form of digitalization would instead be positively associated with more precarious forms of working arrangements, such as solo self-employment with one client and collaborators. Conversely, we expect that a ‘transformative’ form of digitalization (Fossen and Sorgner 2021) is accompanied by an opportunity-driven increase in those types of self-employment that are less vulnerable and an increase in paid employees, on the one hand, and a reduction in the shares of solo self-employment with one client and of collaborators, on the other hand. Understanding the overall context, thus, is important to interpret the nature of the technology: this is why we will complement our findings about self-employed workers with those on all the employees and on firms’ collaborators.

Although the literature on self-employment is very rich, there are still few empirical studies on the relationship between new digital technologies and self-employment dynamics. The existing evidence confirms the co-existence of opportunity- and

⁴ Guzman and Stern (2020) show that incorporated businesses can be associated with opportunity-related objectives as these companies tend to perform better, *ceteris paribus*.

⁵ In Italy, solo self-employed people are often dependent on a single client, and this exposes them at high risks of economic insecurity (Boeri et al. 2020; Muehlberger and Pasqua 2009).

necessity-driven motivations as well as of ‘destructive’ and ‘transformative’ technologies. The relative strengths of the mechanisms at play depend on technology- and worker-related characteristics, as well as on the general economic context.

Sorgner and Fritsch (2018) explore the occupational pathways to entrepreneurship due to technological progress and show that the occupational environment strongly influences the decision to become self-employed. In particular, the magnitude the effect depends on the risk of becoming unemployed (e.g., a push factor), and this varies across occupations and firms. Fossen and Sorgner (2021) show that ‘transformative’ digitalization and ‘destructive’ digitalization exert different effects on self-employed people with and without employees. Transformative forms of digitalization such as those associated with AI make the transition of educated individuals into self-employment without employees less likely and the transition into self-employment with employees more likely, in line with opportunity-driven motivations.

Also Kim et al. (2025) show that the exposure to AI is associated with fewer transitions into solo self-employment, whereas the opposite holds for occupations exposed to industrial robots. This suggests that AI technologies are associated with opportunity-driven transitions, whereas automation and robotics with necessity-driven transitions. Fossen and Sorgner (2022) find that workers in occupations that are more susceptible to destructive digitalization tend to set up unincorporated businesses, whereas those in occupations exposed to transformative digitalization are more likely to be self-employed with employees. Zhang et al. (2022) find that digitization is associated with opportunity-driven entrepreneurs, and that this relation increasingly strengthens with the age of the workers.

Studying worker-level data from 30 European countries, Bachmann et al. (2025) reach different conclusions from Fossen and Sorgner (2021) and Kim et al. (2025). For instance, they find that labour-augmenting technologies (such as AI) increase the probability that individuals move from paid employment into solo self-employment. This effect is related to necessity-driven motivations because its extent is found to be larger for low-skilled paid workers. No significant effects are detected for the transitions into self-employment with employees. Using firm level data, Bessen et al. (2023) find that automation technologies increase the likelihood of working separation, but do not make the transition into self-employment more likely, in contrast with the results found by Kim et al. (2025). This suggests that the destructive nature of automation technologies may offset both the push and pull factors that would lead to greater transitions.

These contrasting findings on the impact of new digital technologies on self-employment dynamics call for further empirical work, and our work aims to contribute to the debate.

Building on the push/pull framework discussed above and on the extant literature, we can formulate a set of directional hypotheses. These latter are not intended to associate a theoretical mechanism with one single coefficient because, as will be explained in Sect. 3, the available data do not allow us to observe entrepreneurial motivations directly. Rather, these hypotheses help to identify empirical patterns across labour-market statuses that are consistent with opportunity-driven and necessity-driven self-employment, as well as with destructive and transformative forms of digitalisation.

The high fixed costs, firm-specific capital, and organisational complementarities that characterise advanced automation tend to increase entry costs to entrepreneurial entry. These features may limit the scope for new entrepreneurial activities, especially for individual workers and small businesses. Big data, by contrast, facilitate access to information and enable data-intensive services, thereby creating business opportunities suitable for independent professionals operating with multiple clients. Hence, we expect big data to be more conducive than advanced automation to opportunity-oriented self-employment.

H1: The adoption of advanced automation (big data) is expected to be associated with lower (higher) opportunity-oriented self-employment, proxied in particular by self-employment with employees and solo self-employment with multiple clients.

Moreover, advanced automation may be associated with a more general worsening of working arrangements if firms rely more heavily on easily substitutable workers who have lower social insurance, wage and job protection, such as dependent self-employed contractors. Big data, conversely, should not increase vulnerable work arrangements if it creates broader market opportunities for truly independent workers capable of serving a larger number of firms.

H2: Advanced automation is expected to increase vulnerable self-employment arrangements, proxied by solo self-employment with only one client, whereas big data is expected not to increase such arrangements.

Finally, the relationship between technology adoption and paid employment helps to interpret the forces behind self-employment dynamics. A reduction in self-employment has different implications depending on whether it is accompanied by expanding paid employment or by stagnant/declining paid employment and rising vulnerable work arrangements.

Taken together, these expectations imply different configurations. Advanced automation should display the pattern of a destructive form of digitalisation (i.e., negative effects on opportunity-oriented self-employment and paid employment, together with positive effects on vulnerable working arrangements), whereas big data should display the pattern of a transformative form of digitalisation (i.e., positive effects on opportunity-oriented self-employment and paid employment, together with negative effects on vulnerable arrangements).

H3: The adoption of advanced automation (big data) is expected to display the pattern of a destructive (transformative) form of digitalisation. Advanced automation should be associated with lower opportunity-oriented self-employment, lower paid employment, and higher vulnerable work arrangements, whereas big data should be associated with higher opportunity-oriented self-employment, higher paid employment, and lower vulnerable work arrangements.

3 Data and Empirical Model

3.1 Data

Data are collected from several sources. Information on the adoption of new digital technologies (the main independent variable) is retrieved from the first wave (ref-

erence year 2018) of the Italian National Institute of Statistics (ISTAT) Permanent Census of Enterprises (Censimento Permanente delle Imprese). The Census combines administrative-level data with survey information on the investment behaviour of firms. In 2019, firms with more than 10 employees were asked about their investments in Industry 4.0 technologies during the period 2016–2018 and this allows us to measure (rather than to infer via proxies) the actual adoption rate of these technologies. This work focusses on two technologies: advanced automation (i.e., collaborative robots and intelligent systems for safety, product quality, and predictive maintenance) and big data technologies (i.e., managing large masses of data in terms of volume, speed, and variety, including through cognitive computing applications such as artificial intelligence, machine learning, and deep learning).

To account for the general equilibrium effects, we aggregate information at the province (NUTS 3) times macro-sector level and the analysis exploits the cross-sectional variation across these cells.⁶ Adoption rates are obtained by dividing the number of adopting firms by the total number of firms in the cell PM , defined by the province P and the macro-sector M . The variables we obtain for advanced automation and big data technologies are called, respectively, $ADV AUTO_{PM}$ and $BIG DATA_{PM}$. The description and sources can be found in Table 4, their descriptive statistics are reported in Table 7 and the distributions of adoption rates are represented in Figs. 1 and 2.

It is worth noticing that this level of analysis of the publicly available data from ISTAT has been adopted in recent studies of other features of the Italian labour markets (Bettarelli and Resmini 2024; Pinate et al. 2024) because it allows to explore both the geographical and sectoral variation at levels that are relevant for both technology adoption and labour mobility.

The dependent variable is built using data from the Italian Labour Force Survey (ISTAT, Rilevazione continua sulle Forze di Lavoro-RFL). Conducted every quarter, the RFL survey depicts the employment status, job-seeking behaviour, and labour market attitudes of Italy's working-age population. Fundamental for our exercise is the question about the type of work that the individual performs. As explained, to operationalize the theoretical channels associated with push/necessity and pull/opportunity motivations driving the transition into self-employment, we explore different sub-groups of self-employed individuals. The RFL survey allows us to identify the self-employed workers, to differentiate between self-employment with and without employees, and the solo self-employed individuals with one client or multiple clients. In addition, we can also identify firms' collaborators.

In line with the data on technology adoption and the medium-to-short-term focus of our analysis, the changes in the local share of self-employed individuals over the

⁶ ISTAT categorizes sectors in five macrosectors: energy and water; total industry excluding construction, energy and water; construction; non-market services; and wholesale and retail trade, repair of motor vehicles and motorbikes.

working-age population are calculated over the period from 2015 and 2019.⁷ Given the goal of our paper, we remove workers in the armed forces (code 8 in the ISTAT classification of occupation CP2011). The description and sources can be found in Table 5 and the descriptive statistics are reported in Table 8.

To address the potential endogeneity of technology adoption, an instrumental variable approach is adopted, borrowing from Caselli et al. (2025a). We build instrumental variables that are based on exogenous measures representing the global technological frontier at the macrosector level for each technology. We interact this latter with a measure of a province-specific factor that captures the cross-province variation in the local capacity to appropriate and adopt external knowledge. This reflects that fact that the actual access to the technology frontier is mediated by the local endowments of human and physical capital and, more generally, by the local absorptive capacity (Caragliu and Nijkamp 2012; Cohen and Levinthal 1990; Keller 2004). Hence, our IVs consist of two elements: first, an exogenous measure of macrosector-specific technological progress at the global frontier (one for each technology); second, its interaction with a characteristic of the province that influences its ability to take advantage of global knowledge (Acemoglu et al. 2006; Caragliu and Nijkamp 2012; Caselli and Coleman 2006; Cohen and Levinthal 1990; Döring and Schnellenbach 2006; Foster and Rosenzweig 2010; Keller 2004).

As for advanced automation, we measure the global knowledge frontier with the relevant industry-level stock of patents, whereas the local absorptive capacity is proxied by the patent intensity at the provincial level in 2012. The industry-level stock of patents is borrowed from Caselli et al. (2024),⁸ while local patent intensity comes from the ISTAT spatial indicators database for development policies. This interaction can be seen as the operationalization of Cohen and Levinthal (1990)'s findings that technology diffusion depends both on global technological progress and on the extent to which new knowledge is recognized, assimilated, and exploited by the firms (that is, on their absorptive capacity). Aggregating at the local level, as discussed by Caragliu and Nijkamp (2012), this implies that insufficient cognitive capital may hamper the absorptive capacity of regions to exploit new knowledge. Hence, the global stock of patents captures the knowledge available outside the local community, and the pre-determined level of local patent intensity proxies for the extent to which local firms are capable of managing the knowledge at the frontier.

Regarding big data technologies, we proxy the global knowledge frontier at the macro-sector level in a different way. As the US has typically been at the forefront of technology adoption in all the domains associated with ICT, software and data analytics, we exploit the past shares of employees in US firms that utilise data analysis

⁷ The state aid measures adopted to help firms to retain their workers during the Covid-19 period (2020–2022) affected labour mobility. Moreover, the extraordinary uncertainty observed during those difficult years hindered the emergence of business opportunities. Accordingly, we prefer not to extend the analysis beyond the year 2019. Similarly, choosing as a base period years before 2015 would have entailed some risks: at that time, Italy was struggling with sovereign debt crisis affecting both economic activities and labour markets. Notably, the analysis is facilitated by the fact that anticipation effects were unlikely: the adoption of digital technologies accelerated considerably only in 2017 after the unexpected introduction of generous tax incentives in the 2017 Italian Budgetary law (approved in December 2016 as part of the Italian Industry 4.0 Plan).

⁸ Patents are associated with 4-digit industries through the correspondence table in Goldschlag et al. (2020).

in 2020, calculated at the macro-sectoral level using the 2021 US Annual Business Survey.

While this measure of the sectoral intensity in adoption in the US can proxy for the global frontier in technology adoption, the extent to which the same phenomenon interested the Italian provinces between 2016 and 2018 depends on their local absorptive capacity. This latter is proxied by the pre-determined local broadband penetration, calculated from the ISTAT spatial indicators database for development policies with 2015 data at the provincial level. According to EIB (2023), the regions with faster internet speed tend to have a higher share of firms adopting digital technologies. Notably, as explained by Benecchi et al. (2023), the Italian government contributed to finance the construction of a fixed broadband infrastructure in those areas where such investment was regarded as unprofitable for private operators. Hence, this variable has the potential to capture connectivity-related capabilities that do not reflect other local characteristics associated with the provincial level of socio-economic development.

The precision of the estimates and the conditional exogeneity of the instrumental variables can be improved with the inclusion of several control variables capturing province- and macrosector-specific characteristics. Hence, we include several controls spanning demographic and economic aspects, business dynamics, investment trends and the like (at the cell, province and macrosector level when possible) that could be correlated with employment outcomes and technology adoption.

The first group of controls regards the demographic and ethnic characteristics at the province level to account for heterogeneous preferences regarding self-employment (Le 1999; Simoes et al. 2016). In particular, we include: the share of foreign-born individuals in 2011, the log of population in 2011, the median age of population in 2015, the dependency ratio in 2015, and the share of the population with tertiary degree in 2015, and the crude rate of natural change of the population in 2015.⁹

To account for the pre-existing economic conditions at the province level, we control for the log of GDP per capita in 2015, the share of local exports in the sectors characterised by more dynamic world demand in 2015, the ratio of the inflow of non-performing loans to the stock of performing loans in 2015, and the share of buildings used for production in 2011.

Given the potential relationship between technology adoption and pre-existing capital stock, we consider the possibility that provinces with a higher initial capital stock may be characterized by more intense technology adoption and greater business opportunities. Controlling for this allows us to identify more clearly the effects of the recent investment in the two digital technologies of interest. Hence, we include in the estimation the average values of fixed capital formation over the period 2010–2015 (normalised by the provincial GDP in 2015) and the ratio of the capital stock over GDP in 2015.

Since the local institutional quality may affect the incentives to start a new business by moving into self-employment, we control for the regulatory quality in the province

⁹ The choice of different years for the lagged values of the controls is due to data availability. The share of foreign-born individuals in 2011, the log of population in 2011 and the share of buildings used for production in 2011 are calculated using the most recent population census before 2015. Other variables come from other databases (see Appendix A for more information about the sources).

in 2015 and we use the index developed by Nifo and Vecchione (2014). We also include the local employment rate in 2015 to account for differences in people's activation.

The estimations would benefit from the inclusion of additional controls that vary across our geographical and sectoral dimensions (PM), as this could help to identify the specific role played by technology adoption. Hence, we include among the controls the location quotient (calculated in 2015) and the share of newly born enterprises in 2015 in each PM cell. The former accounts for the pre-existing industrial structure of the region, and the latter allows for heterogeneous trends in self-employment due to specific features of economic dynamism at the province-macrosector level.

Finally, we account for non-technological investments at the regional (as provincial data are not available) and sectoral level by adding to the specification both the percentage increase in the average fixed capital investment from 2013–2015 to 2016–2018, and the logarithm of the average investments in fixed capital in 2016–2018. Notably, these two covariates are contemporaneous to the period in which technology adoption is measured. Thus, their inclusion helps us to control for any contemporaneous investment spree at the macrosector and regional level; this considerably strengthens also the conditional exogeneity of the instrumental variables. This is a conservative choice because it may lead to estimates that are a lower-bound of the overall impact of the digital technologies of interest.

After dropping the observations for which patent intensity is missing, the final dataset includes 101 provinces and consists of 505 observations representing cells defined by the province P and the macrosector M . A detailed description of these variables and of their sources is in Appendix A, namely in Tables 6 and 9.

3.2 Empirical Model

For each technology, we estimate the following model:

$$\Delta Self - Employment_{OPM} = \alpha + \beta_j O T A_{PM}^j + \mathbf{C}^T \beta_C + \epsilon_{OPM} \quad (1)$$

for $j \in \{\text{Advanced automation, Big data}\}$.

The outcome variable $\Delta Self - Employment_{OPM}$ is the change observed between 2015 and 2019 in the ratio of the number of self-employed workers of type O within province P and macrosector M over the total local working age population.¹⁰

In line with the conceptual background illustrated in Sect. 2, we consider five groups of self-employed workers. The first one is the broadest one and consists of all self-employed workers. This can be split in two sub-groups: self-employed workers with employees and self-employed workers without employees (a.k.a. solo self-employed workers). According to the literature, individuals who transit into solo self-employment are more likely to be driven by necessity because their business activity is limited in size. An additional characteristics can help to identify the most vulnerable (often referred to as bogus) forms of self-employment, that is the number

¹⁰ More formally, $\Delta Self - Employment_{OPM} \equiv \frac{E_{OPM}^{2019}}{LF_P^{2019}} - \frac{E_{OPM}^{2015}}{LF_P^{2015}}$, where E_{OPM} is the number of workers in the triple OPM , and LF_P is the working age population (between 14 and 66 years old) in province P .

of clients with which the self-employed individual entertains business relationships. Self-employed workers without employees, in fact, can have either multiple clients or only one client. Those with only one client are extremely dependent and vulnerable for the reasons discussed in Sect. 2: this suggests that these positions are associated with transitions driven by necessity.

These outcome variables map directly into the hypotheses formulated in Sect. 2: self-employment with employees and solo self-employment with multiple clients proxy opportunity-oriented self-employment, while solo self-employment with only one client proxy more vulnerable arrangements.

We estimate the effects also on other groups of workers, namely all the employed workers and collaborators. Estimating the effects on the ratio of all employees over the working age population helps us to identify the overall employment effects of technological adoption and to contrast it with the effects on the different types of self-employment. Collaborators are part of a specific group of non-standard parasubordinate workers who suffer of weak and vulnerable arrangements as the solo self-employed people with only one client also do.¹¹

The interpretation of the entire set of empirical results for all the groups of workers allows us to shed some light on the destructive vs transformative nature of these two digital technologies.

The variable TA_{PM}^j stands for the local adoption rate and consists in the share of firms that adopt the technology j , either advanced automation or big data, at the PM level in the period from 2016 to 2018. The matrix $\mathbf{C}^T$ corresponds to the set of controls measured at either the province (P) or the province $\times$ macrosector (PM) level with a time lag. This set contains demographic characteristics, as well as measures of economic activity, business dynamics, institutional quality and capital stocks. Matrix $\mathbf{C}^T$ also includes the percentage increase in the average fixed capital investment from 2013–2015 to 2016–2018, and the logarithm of the average investments in fixed capital in 2016–2018. These two covariates are contemporaneous to the period in which technology adoption is measured. Their inclusion helps us to control for any contemporaneous investment spree at the macrosector and regional level. Moreover, as explained in Sect. 3.1, this strengthens the conditional exogeneity of our instrumental variables as it allows us to condition the estimates on the presence of any macrosector $\times$ region-specific difference in the firms' propensity to invest. Notably, this represents a conservative choice and our estimates conditional on these controls may be a lower-bound of the overall impact exerted by the digital technologies. Finally, the specification includes the covariates (i.e., local patent intensity and local broadband penetration) used as interacting terms in the instrumental variables (more on this below). All these control variables were described in detail in Sect. 3.1.

The standard errors in the estimations are clustered at the province level to account for possible cross-sectoral effects within a province.

¹¹ Collaborators are of particular interest in Italy because, for a long period of time, there has been a tendency to abuse their use with a view to establishing quasi-exclusive employment relationships with limited protection. Although their number decreased after the implementation of the Fornero Reform (Italian Law 92/2012) and of the 2015 Jobs Act encouraging the use of temporary job contracts (Bovini and Viviano 2018), thereby making solo self-employment with one client the main alternative to paid employment, this group remains of help to draw a broader picture of the effects of these digital technologies.

Despite the large number of control variables included in the specification, OLS estimates of the coefficients of interest could still suffer from endogeneity due to unobserved factors affecting both the adoption rates and the self-employment dynamics. For instance, positive demand shocks could boost both technological investments made by incumbent firms and new business opportunities for new entrepreneurs. Hence, we adopt the instrumental variable (IV) strategy used in Caselli et al. (2025a) and estimate the functional form with the IV-2SLS method.

As anticipated, the identification strategy is based on two elements. The first one is the use of a proxy of the global knowledge frontier in a technology domain and in a macrosector, which individual Italian firms may gain access to before adopting novel technological solutions. The greater the exogenous stock of global knowledge in the macrosector, the more likely is firm's adoption. The second element is a measure of the local endowment of human and physical capital, and more generally, of the local absorptive capacity that mediates firms' access to the knowledge frontier (Caragliu and Nijkamp 2012; Cohen and Levinthal 1990; Keller 2004). In sum, the larger is the global stock of knowledge and the more capable is a province of accessing it, the more likely technology adoption becomes.

As anticipated, we operationalise this economic intuition about the process of technology diffusion in different ways for the two technologies. The global knowledge frontier for advanced automation is measured as the number of robotics-related patents granted from 2000 to 2014 and the local absorptive capacity is proxied by provincial patent intensity measured in 2012. For big data, the global knowledge frontier is captured by the share of employees in US firms adopting technologies for data analysis in 2020 (as indicated in the Annual Business Survey 2021 by the US Census Bureau), and the local broadband penetration in 2015 proxies for local absorptive capacity. We refer to Sect. 3.1 for a discussion.

We maintain that our macrosector-specific proxies of the global knowledge frontier in each technology domain can be considered as exogenous because they do not depend on contemporaneous Italian factors. However, they could be correlated with other omitted macrosector-specific phenomena that directly relate to technological adoption and to transitions into self-employment. To reduce this risk, we include among the controls several covariates, and in particular the non-technological investments at the regional and macrosectoral level, that make our instrumental variables more likely to be conditional exogenous.¹²

4 Results

Table 1 shows the estimates of the effects of advanced automation on the changes in the shares of different sub-groups of self-employed individuals. In column 1, we find a negative and significant effect for the entire group of self-employed workers.

Such negative effect of advanced automation on self-employed workers is consistent with the idea that, despite its inherent displacement effects on paid workers,

¹² To ensure conditional independence of the instruments, we always include the variable proxying for absorptive capacity in the estimation too.

advanced automation creates very limited business opportunities in self-employment. This is probably due to the high fixed costs associated with its adoption in brand new companies (Bijmens and Konings 2020). A negative relationship is inconsistent with dominant push/pull channels in gross flows and it implies that necessity- and opportunity-related effects do not translate into higher shares of self-employed workers. While this is *prima facie* evidence about the destructive nature of the technology, the analysis of the sub-groups of workers is necessary to draw more solid conclusions about it.

To shed further light on the underlying mechanisms, thus, we look at the differentiated impact of advanced automation on the self-employed workers with and without employees, as the latter can be considered as quasi-employees without the privileges of being paid employees (Cieřlik and van Stel 2024). The decomposition of the broad group in the self-employed workers with employees (column 2) and without employees (column 3) shows that the overall negative effect is entirely driven by the solo self-employed individuals, whereas the share of self-employed people with employees in a *PM* cell is not significantly related to the adoption of advanced automation. This is additional evidence that advanced automation discourages opportunity entrepreneurship for individual workers.

It is possible to learn more by looking at what happens to the most ‘dependent’ self-employed workers, namely the solo self-employed with only one client (Boeri et al. 2020; Böheim and Mühlberger 2009; Muehlberger and Pasqua 2009).¹³

The estimated coefficient for the solo self-employed workers with only one client (column 5) is positive and significant, in line with previous findings by Muehlberger and Pasqua (2009). The coefficient for the solo self-employed individuals with multiple clients (column 4), instead, is negative and significant. These estimates suggest that advanced automation reduces the overall share of solo self-employed people but boosts the most vulnerable ‘dependent’ self-employed positions. These results confirm the complementarity between advanced automation and flexible labour arrangements found by Damiani et al. (2023); Lewandowski and Szymczak (2025) and Traverso et al. (2025).

The results in Table 1 are therefore consistent with H1 and H2 for advanced automation: advanced automation does not increase opportunity-oriented self-employment and is associated with a higher share of solo self-employed workers with a single client.

It could be argued that the adoption of advanced automation may attract more stable paid employees and this may increase the opportunity cost of entrepreneurship, thereby reducing the share of self-employed workers. If this were correct, advanced automation would act as a ‘transformative’ technology, capable of reducing the appeal of entrepreneurship due to its very positive effects on paid positions. Our estimates on the sub-groups suggest to conclude against this interpretation. The estimates for the impact of advanced automation on all the employees are negative, although not significant (see column 3 in Table 3), and this is at variance with an improvement of paid employment positions (and an increase in the opportunity cost of entrepreneurship)

¹³ Bogus self-employment is a further subclass of very fragile dependent self-employed people and it consists of workers who are disguised as self-employed people only to allow the principal to avoid granting the protections due to the paid employees (Román et al. 2011; Cieřlik and van Stel 2024).

and, rather, it is in accordance with significant displacement effects. Moreover, the data suggest that advanced automation is mildly associated with the growth of collaborators (column 1 of the same Table), who have low protection and wages. Notably, the effect is similar in magnitude to that exerted on the shares of the dependent self-employed workers. This suggests a penalization of long-lasting contractual relationships due to the adoption of advanced automation.

Taken together, the evidence is broadly consistent with H3 for advanced automation: the technology displays the pattern of a destructive form of digitalisation (Fossen 2021), as it is associated with an overall deterioration of working arrangements, no evidence of employment expansion, and limited opportunity-driven transitions into entrepreneurship.

The estimates for big data are shown in Table 2. We find that the adoption of big data boosts self-employment (column 1), in particular solo self-employed workers (column 3). At first sight, these positive relationships could support the idea that big data promotes opportunity-driven transitions into self-employment. Big data technologies are more likely than advanced automation to create new products, tasks, and business models, thereby making paid employees choose self-employment to seize new business opportunities.

In fact, whether the new self-employed individuals can truly be considered as opportunity entrepreneurs is not clear cut. On the one hand, we find no positive impact on the self-employed individuals with employees, and this could be a signal of limited growth opportunities for the companies born out of big data. On the other hand, the effect on solo self-employed individuals with only one client (most directly proxying the necessity-driven entrepreneurs) is not significant (column 5 of Table 2), thereby supporting the opportunity-based interpretation.

Accordingly, the results in Table 2 provide some support for hypotheses H1 and H2 with regard to big data. It is plausible that the increase in self-employment associated with the adoption of big data is opportunity-based, although the impact on the self-employed individuals with employees is muted.

We resort to additional pieces of evidence to draw some tentative conclusions about the nature of big data. First, this technology is associated with an increase in almost all types of employees (see column 4 in Table 3); second, its impact on the collaborators is negative (see column 2 in Table 3). These findings are in line with Lewandowski and Szymczak (2025), who conclude that software and databases increase total employment and are neutral for atypical employment.

If one combines all these findings together (and also with the observation that the working-age population generally increased during the period), big data seems to have an overall positive effect on the labour markets, with more business opportunities, better working arrangements and a lower scope for necessity entrepreneurship, in line with previous findings (Acciarini et al. 2023). This supports hypothesis H3, that is the view that big data is a ‘transformative digitalization’, to use Fossen and Sorgner (2021)’s jargon.

It is worth noticing that both technologies exert stronger effects on solo self-employed individuals. This corroborates previous conclusions by Bento and Restuccia (2025). This also strengthens the importance of studying the changes in solo self-employment when looking at business dynamism. As business data and employment

data do not perfectly overlap, a joint analysis of both sources of information (and, possibly, their combination) is warranted.

On a technical note, our main results are based on an IV-2SLS estimation method that passes the principal validity tests.¹⁴ The data fail to reject that the instruments are exogenous (Hansen J test) and the tests reject that they are not relevant (Kleibergen–Paap rk LM statistic).¹⁵

We acknowledge that the use of broad macro-sectoral aggregates in the construction of the *PM* cells may mask some heterogeneity in technology exposure and labour market adjustments across industries. The attenuation bias this creates may affect the identification of the coefficients and of the underlying mechanisms. The decision to use this level of aggregation depends both on an empirical motivation and a theoretical reason. At the empirical level, the representativeness of the provincial (NUTS 3) data in the Italian Labour Force Survey is not guaranteed at a lower level of sectoral aggregation; moreover, the data from the Census are not publicly available at a lower level of industrial aggregation. At the theoretical level, the use of broad macro-sectoral aggregates is in line with recent studies that explore firm's activities and/or workers' mobility along the geographical and sectoral dimensions (see, for instance, Galle et al. 2023; Intraligi et al. 2024; Moretti and Yi 2024). The underlying idea is that workers' mobility across the macrosectors is far lower than within a macrosector. As far as the geographical dimension is concerned, it is important to keep the analysis at a level that is as close as possible to the local labour markets, and this prevents us from using regional (NUTS 2) data for which we could have retrieved data at a more granular level of sectoral aggregation.

Furthermore, it is worth recalling that the great majority of the studies focusing on technology and employment dynamics do not consider any sectoral disaggregation, whereas they exploit exclusively the regional dimension at the level as close as possible to local labour markets (see, for instance, Acemoglu and Restrepo 2020; Autor et al. 2013; Caselli et al. 2025b; Dauth et al. 2021; Dottori 2021 among the many). Hence, the exploitation of the variation across macrosectors represents a further contribution of this work to the existing literature.

This notwithstanding, we performed some auxiliary estimations (available upon request) to see whether the results change once the effect of technology adoption on self-employment is allowed to differ across provinces that exhibit a relatively

¹⁴ We performed a robustness test using the limited information maximum likelihood estimator instead of the IV-2SLS (Burgess et al. 2017). The findings are fully consistent with our main specification. The results are available upon request.

¹⁵ In fact, the estimates for the effects of big data on self-employed workers with employees and on collaborators fail the Hansen J test. We apply the procedure in Nevo and Rosen (2012) to calculate the upper bound and the confidence interval of the parameter of interest when the instrument does not satisfy the exogeneity condition but the instrument is less endogenous than the explanatory variable. The main conclusions are confirmed. The upper bound for the effects of big data on collaborators is negative (-0.0026) and the confidence interval does not contain zero. For the self-employed individuals with employees, the confidence interval includes zero, although the point estimate is negative (-0.0036).

Table 1 Advanced automation

	(1) Self-employed	(2) Self-employed with employees	(3) Self-employed without ees	(4) Self-employed without employ- ees and more than one client	(5) Self-employed without employ- ees and only one client
<i>ADVAUTOPM</i>	-0.0412** (0.0207)	0.0029 (0.0096)	-0.0441** (0.0174)	-0.0540*** (0.0178)	0.0099** (0.0044)
Observations	505	505	505	505	505
Controls	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap rk LM statistic	30.7289	30.7289	30.7289	30.7289	30.7289
Kleibergen-Paap rk LM statistic p value	0.0000	0.0000	0.0000	0.0000	0.0000
Hansen test chi2	1.6539	0.0011	1.9562	2.4111	0.8840
Hansen test p value	0.1984	0.9733	0.1619	0.1205	0.3471

Types of self-employment. IV-2SLS estimates. The table presents the IV-2SLS regression estimates for self-employed workers on the adoption of advanced automation technologies. Outcome variables are calculated as shares of the working-age population in each province. The table distinguishes between different types of self-employment: total self-employment; with and without employees; self-employment without employees with only one client; and self-employment without employees with more than one client. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 2 Big data

	(1) Self-employed	(2) Self-employed with employees	(3) Self-employed without employ- ees	(4) Self-employed without employ- ees and more than one client	(5) Self-employed without employ- ees and only one client
<i>BIGDATA PM</i>	0.0531*** (0.0151)	0.0059 (0.0076)	0.0472*** (0.0117)	0.0460*** (0.0111)	0.0012 (0.0033)
Observations	505	505	505	505	505
Controls	Yes	Yes	Yes	Yes	Yes
Kleibergen–Paap rk LM statistic	29.3873	29.3873	29.3873	29.3873	29.3873
Kleibergen–Paap rk LM statistic p value	0.0000	0.0000	0.0000	0.0000	0.0000
Hansen test chi2	1.4231	7.8605	0.0022	0.0233	0.2147
Hansen test p value	0.2329	0.0051	0.9624	0.8787	0.6431

Types of self-employment. IV-2SLS estimates. The table presents the IV-2SLS regression estimates for self-employed workers on the adoption of big data technologies. Outcome variables are calculated as shares of the working-age population in each province. The table distinguishes between different types of self-employment: total self-employment; with and without employees; self-employment without employees with only one client; and self-employment without employees with more than one client. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3 Advanced automation, big data: employees and collaborators

	(1)	(2)	(3)	(4)
	Collaborators advanced automation	Collaborators big data	Employees advanced automation	Employees big data
<i>ADV AUT_{PM}</i>	0.0162*** (0.0044)		−0.0191 (0.0411)	
<i>BIG DAT_{PM}</i>		−0.0072*** (0.0023)		0.0526** (0.0240)
Observations	505	505	505	505
Controls	Yes	Yes	Yes	Yes
Kleibergen–Paap rk LM statistic chi2	30.7289	29.3873	30.7289	29.3873
Kleibergen–Paap rk LM statistic p value	0.0000	0.0000	0.0000	0.0000
Hansen test chi2	0.0309	6.8913	0.5905	2.0990
Hansen test p value	0.8605	0.0087	0.4422	0.1474

IV-2SLS estimates. The table presents the IV-2SLS regression estimates of Collaborators and Employees on the adoption of advanced automation and big data technologies. Outcome variables are calculated as shares of the working age population in the province. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1

higher/lower share of industries that are particularly exposed to these technologies.¹⁶ The estimates remain consistent with those commented above and no significant heterogeneity is detected.

5 Closing Remarks

This work provides new causal evidence on how the adoption of advanced automation and big data affects self-employment dynamics in Italy.

The main finding is that the two technologies produce opposing effects, primarily by affecting the solo self-employed. Advanced automation is associated with a decrease in the share of solo self-employed workers and with an increase in the share of vulnerable ‘dependent’ self-employed workers and collaborators. These findings suggest that advanced automation may contribute to a potential deterioration of working arrangements, consistent with a ‘destructive’ form of digitalization as indicated by Fossen (2021) and Kim et al. (2025). Big data, by contrast, produces positive effects on solo self-employed individuals, in particular those with multiple clients, while reducing the share of collaborators. These estimates, together with the positive effect found for all the employees, indicate that big data tends to be a ‘transformative’ technology associated with more opportunity-driven entrepreneurship.

This study contributes to the literature by revealing the divergent impacts of these technologies across distinct groups of self-employed individuals, using a sufficiently granular classification to shed light on issues that remain debated. Moreover, by exploiting geographical and sectoral data on technology adoption, the analysis takes into account the actual diffusion of each technology across macrosectors and Italian provinces, thereby adding to previous analyses based on indirect measures of potential occupational exposure. The two approaches represent complementary evidence on the issue. On the one hand, our analysis does not differentiate paid and self-employed workers in terms of their occupational exposure before the transition into self-employment, which prevents us from examining how workers’ skills, occupational tasks and technology characteristics interact. On the other hand, we move beyond measures of potential exposure by considering the extent to which a technology is locally adopted, thereby reducing the risk that potential exposure may proxy for other unobserved occupation-specific factors.

One limitation of the analysis is the short time span covered by the data, which prevents us from examining longer-run dynamics. Extending the analysis to the COVID-19 period and its immediate aftermath is problematic because the pandemic may have represented a structural break in firms’ approaches to technology adoption and human-resource management, as well as in individuals’ self-employment decisions. The implications of these changes are nevertheless uncertain. On the one hand, there is evidence of continued digital adoption among small and medium-sized firms,

¹⁶ For advanced automation, we considered the local share of light manufacturing firms and the local share of automotive firms, as often done in this literature. For big data, we considered the local share of firms in ICT sectors. In each case, we created a dummy variable indicating whether a province exhibits a share higher than the median and we interacted it with the corresponding variable capturing the adoption rate. Significant interactions would point toward heterogeneous effects.

together with a broader diffusion of remote-working arrangements (Istituto Nazionale di Statistica 2023, 2025). These developments suggest an increasing demand for autonomy at work, which could have also fostered transitions into self-employment. On the other hand, one can observe a diffusion of advanced welfare programmes to attract and retain experienced and skilled workers, which could have worked in the other direction. Further research covering more recent periods is therefore warranted as suitable data become available.

A further limitation of the analysis arises from potential misreporting in the RFL survey, for instance due to the ambiguity of the definition of a client. Given the heterogeneity of business relationships between firms and external contractors, some measurement error cannot be excluded. Should such errors be correlated with technology adoption across locations and sectors, they could generate attenuation bias.

Although the use of provincial and broad macro-sectoral aggregates is in line with recent studies exploring workers' mobility along both the geographical and sectoral dimensions, we acknowledge that broad macrosectors may hide some heterogeneity in technology exposure and labour market adjustments across industries. Our chosen level of aggregation reflects three considerations: the representativeness requirements of the Italian labour force survey, the public availability of Census data, and the objective of using geographical units that approximate local labour markets as closely as possible. This notwithstanding, we acknowledge that our estimates, as well as those of the studies on technology and employment dynamics that consider only the variation in the regional dimension, may be subject to attenuation bias.

Public authorities, and the European Commission in particular, have expressed concerns about the consequences of a technology-induced increase in solo self-employment. Because they are generally excluded from traditional collective-bargaining arrangements, these workers may have limited bargaining power and risk facing unfavourable contractual conditions. Our study shows that the widespread adoption of advanced automation may be particularly troublesome because it tends to be associated with a worsening of working arrangements and few opportunity-driven transitions into self-employment.

As pointed out by OECD (2019), the misclassification of workers to circumvent regulatory and tax requirements on paid employees may have serious negative implications for individual workers and on working conditions more generally. Such misclassification could imply an implicit shift in the distribution of risk in society and could weaken workers' bargaining power. The relevance of this concern depends partly on the extent to which entitlements and contributions remain tied to standard/paid employment. Our analysis cannot shed light on this issue directly because we lack the information required to distinguish bogus from genuine self-employment. By showing that technological innovation affects the composition of paid and self-employed work, however, our results highlight the importance of strengthening monitoring in response to major technological shocks, particularly those associated with destructive forms of digitalization.

We do not claim that self-employment should be discouraged per se. In fact, this form of employment may reflect new business opportunities and it can help to activate otherwise marginalized groups. Rather, as observed by Cieřlik and van Stel (2024), self-employed people need to be properly regulated and supported, instead of

being considered as mere deviations from the traditional categories of employee and employer. Policymakers could sharpen their tools to identify and discourage dependent and bogus self-employment. The International Labour Organization (ILO) has already called for measures targeting these situations, in particular where disguised employment relationships are widespread or increasing. Indeed, the approaches adopted so far in the OECD countries cut across various policy dimensions: new regulatory initiatives, revisions of the tax treatment of standard employees and unincorporated self-employed contractors (so as to reduce differentials and discrepancies), ad hoc monitoring practices (for instance via specialised teams within the labour inspectorates), simplification of enforcement procedures in cases of suspected misclassification, and extension of social and labour law protection to self-employed people (OECD 2019). In 2024, the US Department of Labor revised its guidance for determining employee versus independent-contractor status under the Fair Labor Standards Act, in view of the implications of misclassification for minimum wages, overtime pay, and other worker protections. In 2017, Italy adopted a regulatory framework for self-employment and, more recently, measures supporting self-employed workers during market transitions were introduced.

Among these interventions, targeted inspections are particularly relevant (OECD 2019). Such interventions require up-to-date information to identify the sectors, regions, and areas of activities that warrant closer scrutiny. In the past, the attention of the Italian authorities has primarily focused on potentially misclassified self-employment positions in the construction industry. In Europe, platform-related activities attracted attention and interventions (Aloisi 2022). Our estimates suggest that the overall picture is nuanced as new digital technologies tend to produce heterogeneous effects. Advanced automation may contribute to the deterioration of working arrangements through two different channels: the increase of dependent self-employed workers and that of collaborators, both more vulnerable than paid employees. Hence, our findings suggest that the authorities should monitor closely those sectors in which advanced automation has been adopted more intensively. By contrast, big data appears to complement workers' skills and create new opportunities for transitions into self-employment, consistent with a transformative form of digitalization. This does not imply that monitoring should cease in sectors intensively adopting big data technologies: our results indicate that big data is not associated with a greater share of self-employed workers with employees, suggesting that the resulting business opportunities may have limited potential for employment growth.

This analysis could be extended to assess whether the effects are contingent on either sectoral or regional characteristics, but this would require more disaggregated data that remain representative at the relevant geographical and sectoral levels. Another possible direction for future work is to examine these mechanisms with individual-level data on transitions from paid to self-employment. This would allow us to explore the interaction between workers' characteristics, job tasks and technology characteristics. Looking at artificial intelligence, Cazzaniga (2024) identifies upward labour market transitions from high-exposure, low-complementarity occupations to high-exposure, high-complementarity occupations. In particular, given the value of accounting for the actual intensity of technology adoption, it would be interesting to explore how *ex ante* measures of occupational exposure can be combined with measures of actual adoption.

A further avenue for research is to examine the long-run persistence of these effects, as this is connected with the potential growth and survival of businesses created out of transitions from paid employment to self-employment. Such an analysis would require data covering a substantially longer time horizon.

Appendix A: Variables

A.1 Description and Sources

See Tables 4, 5, and 6.

Table 4 Variables: technology adoption variable

Variables	Description	Source
$ADVAUTOPM$	Adoption rate of Adv. automation in $P \times M$, 2016–2018	CPI
$BIGDATAPM$	Adoption rate of Big data in $P \times M$, 2016–2018	CPI

P NUTS 3 provinces, M macrosectors, CPI Italian Permanent Census of Enterprises

Table 5 Variables: employment-related variables

Variables	Description	Source
$\Delta Self - Employment_{PM}$	Change (2019–2015) in the ratio of self-employed workers in $P \times M$ over the local working age population	RFL
$\Delta Self - Employment_{PM}^{NonSolo}$	Change (2019–2015) in the ratio of self-employed workers with employees in $P \times M$ over the local working age population	RFL
$\Delta Self - Employment_{PM}^{Solo}$	Change (2019–2015) in the ratio of self-employed workers without employees in $P \times M$ over the local working age population	RFL
$\Delta Self - Employment_{PM}^{Solo, 1Client}$	Change (2019–2015) in the ratio of self-employed workers without employees and only one client in $P \times M$ over the local working age population	RFL
$\Delta Self - Employment_{PM}^{Solo, >1Client}$	Change (2019–2015) in the ratio of self-employed workers without employees and more than one client in $P \times M$ over the local working age population	RFL
$\Delta Employees_{PM}$	Change (2019–2015) in the ratio of employees in $P \times M$ over the local working age population	RFL
$\Delta Collaborators_{PM}$	Change (2019–2015) in the ratio of collaborators in $P \times M$ over the local working age population	RFL

P NUTS 3 provinces, M macrosectors, RFL Italian Labour Force Survey

Table 6 Variables: control variables and instrumental variables

Variables	Description	Source
<i>Control variables</i>		
<i>lPopp</i>	ln (Total resident population in P, Y = 2011)	CPA
<i>Dependency_Ratio_p</i>	Pop. with age (14 ≤ ≤ 65)/Pop. in P, Y = 2015	Eurostat
<i>Age_Popp</i>	Median age of population in P, Y = 2015	Eurostat
<i>PopGrowth_p</i>	Crude rate of change of population in P, Y = 2015	Eurostat
<i>Foreigners_Share_p</i>	Foreigners/total population in P, Y = 2011	Eurostat
<i>High_Education_Share_p</i>	Share of pop. with tertiary educ. in P, Y = 2015	RFL
<i>lGDP_PC_p</i>	ln (GDP per capita in P, Y = 2015)	Eurostat
<i>CapitalGDP_Ratio_p</i>	Capital stock/GDP in P (constant prices), Y = 2015	Ardeco
<i>NewFCapitalGDP_Ratio_p</i>	Gross fixed capital formation (Avg 2010–2015)/GDP in P, Y = 2015	Ardeco
<i>BusBuildings_Share_p</i>	Buildings in production/buildings in P, Y = 2011	CPA
<i>Employment_Rate_p</i>	Employment rate in P, Y = 2015	RFL
<i>Export_Capacity_p</i>	Share of local exports in sectors with dynamic global demand (%) in P, Y = 2015	ISTAT(BDTPS)
<i>Regulatory_Quality_p</i>	IQI dimension of regulatory quality in P, Y = 2015	IQI
<i>Credit_risk_p</i>	Ratio of inflows of non performing/performing loans in P, Y = 2015	ISTAT(BDTPS)
<i>Location_Quotient_{pM}</i>	Firm-based Location quotient in P×M, Y = 2015	ASIA
<i>NewEnterprises_Share_{pM}</i>	New Enterprises/All Enterprises, in P×M, Y = 2015	Eurostat
<i>Growth_CapitalInvestment_{RM}</i>	Average growth rate of investments in fixed capital in R×M: (avg inv. (2016 to 18)- avg inv. (2015 to 2013)) / avg inv. (2015 to 2013)	ISTAT(FCD)

Table 6 continued

Variables	Description	Source
<i>Level_CapitalInvestment_{RM}</i>	ln(Average investments in fixed capital from 2016 to 2018) in $R \times M$	ISTAT(FCD)
<i>Controls and interaction terms with the IVs</i>		
<i>BroadBand_p</i>	Broadband penetration in P, Y = 2015	ISTAT(BDTPS)
<i>Patent_Intensity_p</i>	Number of patents (EPO) over pop. in P, Y = 2012	ISTAT(BDTPS)
<i>Instrumental variables—IV</i>		
<i>Number_of_patents_AdvAuto_M</i>	Number of robotics related patents granted from 2000 to 2014	Caselli et al. (2024)
<i>US_DataAnalysis_Empl_pct_M</i>	Share of employees in US firms adopting technologies for big data analysis in 2020	ABS2021

P NUTS3 provinces, *R* NUTS2 regions, *M* macrosectors, *Y* years, *ABS2021* Annual Business Survey 2021 by the US Census Bureau, *ARDECO* Annual Regional Database of the European Commission, *ASIA* Registro statistico delle imprese attive, *CPA* Italian Population Census 2011, *EPO* European Patent Office, *GDP* gross domestic product, *IQI* Institutional quality index-IQI Dataset, *ISTAT(BDTPS)* ISTAT spatial indicators database for development policies, *ISTAT(FCD)* ISTAT dataset on fixed capital investments, *RFL* Italian Labour Force Survey

A.2 Descriptive Statistics

See Tables 7, 8, 9 and Figs. 1, 2.

Table 7 Descriptive statistics: technology adoption variables

	(1) N	(2) Mean	(3) Sd	(4) Min	(5) Max
<i>ADVAUTO_{PM}</i>	505	3.5096	3.9087	0.0000	22.2222
<i>BIGDATA_{PM}</i>	505	3.7649	4.2380	0.0000	45.4545

The table reports descriptive statistics (number of observations, mean, standard deviation, minimum, and maximum) for Technology adoption variables

Table 8 Descriptive statistics: employment-related variables

	(1) N	(2) Mean	(3) Sd	(4) Min	(5) Max
$\Delta Self - Employment_{PM}$	505	0.0028	0.5884	-1.7968	2.7194
$\Delta Self - Employment_{PM}^{NonSolo}$	505	-0.0248	0.2651	-1.1576	1.0515
$\Delta Self - Employment_{PM}^{Solo}$	505	0.0276	0.4784	-1.6682	2.5016
$\Delta Self - Employment_{PM}^{Solo, > IClient}$	505	0.0782	0.4516	-1.4069	2.4934
$\Delta Self - Employment_{PM}^{Solo, > IClient}$	505	-0.0507	0.1479	-0.7733	0.6007
$\Delta Employees_{PM}$	505	0.6113	1.1978	-2.2041	6.4296
$\Delta Collaborators_{PM}$	505	-0.0554	0.1349	-0.8857	0.2961

The table reports descriptive statistics (number of observations, mean, standard deviation, minimum, and maximum) for Employment-related variables

Table 9 Descriptive statistics: control and IV variables

	(1) N	(2) Mean	(3) Sd	(4) Min	(5) Max
<i>Control variables</i>					
$lPop_p$	505	12.9844	0.6969	11.3764	15.2012
$Dependency_Ratio_p$	505	57.1931	5.8885	48.0000	99.4000
Age_Pop_p	505	46.3188	5.0644	40.7000	92.7000
$PopGrowth_p$	505	-3.7604	2.4197	-12.2000	1.9000
$Foreigners_Share_p$	505	0.0672	0.0324	0.0123	0.1347
$High_Education_Share_p$	505	14.3228	2.9986	8.6492	23.2493
$lGDP_PC_p$	505	10.1251	0.2676	9.5956	10.8493
$CapitalGDP_Ratio_p$	505	3.8466	1.2512	1.8913	7.1978
$NewFCapitalGDP_Ratio_p$	505	0.1740	0.0157	0.1486	0.2140
$BusBuildings_Share_p$	505	11.5409	3.0887	5.7925	28.9412
$Employment_Rate_p$	505	57.1976	9.9607	36.0836	71.1113
$Export_Capacity_p$	505	29.9521	20.8956	0.5843	87.7549
$Regulatory_Quality_p$	505	0.5178	0.2324	0.0000	1.0000
$Creditrisk_p$	505	4.5387	1.8311	0.9678	13.1258
$Location_Quotient_{PM}$	505	1.0337	0.3571	0.4300	6.7907
$NewEnterprises_Share_{PM}$	505	6.2896	1.9128	2.3163	12.2287
$Growth_CapitalInvestment_{RM}$	505	0.1806	0.2416	-0.3718	1.2030
$Level_CapitalInvestment_{RM}$	505	7.2493	1.5446	3.0850	10.4579

Table 9 continued

	(1) N	(2) Mean	(3) Sd	(4) Min	(5) Max
<i>Controls and interaction terms with the IVs</i>					
<i>BroadBandp</i>	505	1.4189	1.5854	0.0031	9.5173
<i>Patent_Intensityp</i>	505	56.3403	74.1435	2.2174	643.5428
<i>Instrumental Variables</i>					
<i>Number_of_patents_AdvAuto_M</i>	505	7,108.33	12,551.13	66.65	32,171.82
<i>US_DataAnalysis_Empl_pct_M</i>	505	53.8771	8.0659	40.0689	62.9891

The table reports descriptive statistics (number of observations, mean, standard deviation, minimum, and maximum) for controls and instrumental variables

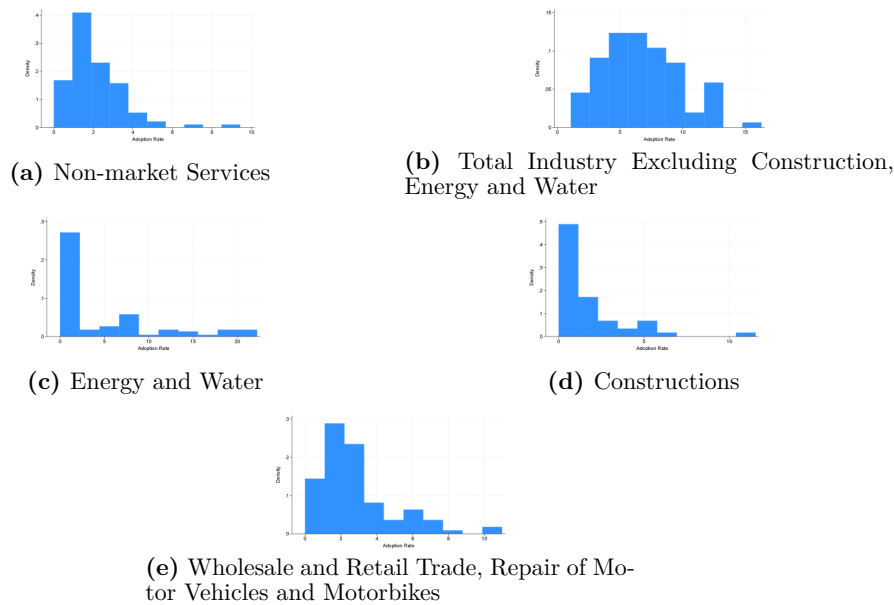


Fig. 1 Advanced automation adoption rate: distribution by macrosectors. The figures show histograms illustrating the distribution of advanced automation technology adoption by macrosectors

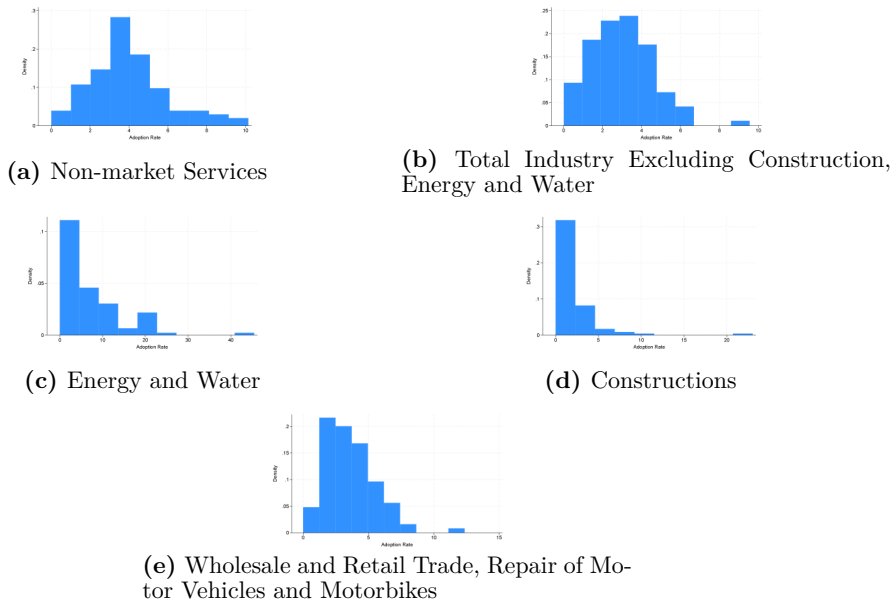


Fig. 2 Big data adoption rate: distribution by macrosectors. The figures show histograms illustrating the distribution of big data technology adoption by macrosectors

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Declarations

Conflict of interest The authors declare that they have no conflicts of interest concerning the submitted article, the journal or their affiliations.

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