Firms That Automate: Evidence & Theory

By JOEL KARIEL*

Which firms are using automation technologies, and what are the effects on firms and the aggregate economy? Using Italian survey data on adoption of cutting-edge technologies, such as Artificial Intelligence, I compile a set of novel findings. Firms that automate are larger, pay higher wages, and are more productive. Technology adopters grow faster once they start using automation technologies. I embed technology adoption in a heterogeneous firm model to investigate the aggregate implications of automation. The model reconciles the firm-level evidence of technology adoption boosting firm size, with the various macro studies suggesting a negative overall effect on employment.
JEL: D22, J23, J24, L11, O14.
Keywords: Automation, Firm Dynamics, Employment, Technology, Productivity.

A recent wave of research has considered the impact of automation technologies, which can perform tasks that - until recently - were limited to the domain of human labour. The sharp increase in the capability and spread of automation technologies has been widely discussed and studied (Acemoglu and Restrepo, 2018*b*; Acemoglu, Lelarge and Restrepo, 2020; Atalay et al., 2018; Dechezleprêtre et al., 2020). Adoption of automation technologies is growing quickly. Robots are an established automation technology, and the *growth rate* of the global stock of robots has been rising rapidly, from around 4% in 2010 to over 15% in 2017 (International Federation of Robotics, 2014). The increased interest and use of Artificial Intelligence has been startling. For example, Fujii and Managi (2018) found the global number of AI-related patents had tripled from 2012 to 2016. However, most of the empirical analysis on such technologies has taken place at a macro level. For example, studies of how national robot adoption has impacted labour markets are quite commonplace (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020; Kariel, 2021).

This paper fills a noticeable gap in the literature by studying the adoption of automation technologies across firms. This research has both empirical and theoretical components. Firstly, I use a unique panel dataset of Italian firms to look at the heterogeneity in adoption, and the impact, of new automation technologies. This data has five main advantages over many existing studies on automation among firms (Kwon and Stoneman, 1995; Bartel, Ichniowski and Shaw, 2007; Dinlersoz and Wolf, 2018; Kromann and Sorensen, 2019; Benmelech and Zator, 2022; Acemoglu, Lelarge and Restrepo, 2020): (1) it includes a wide range of cutting-edge automation technologies, (2) there is infor-

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I thank my colleagues at the University of Oxford for feedback during internal seminars. I also thank participants from RES 2021, RGS Doctoral Conference 2021 and EBES 2021 for their helpful comments. Finally I thank my DPhil supervisor Petr Sedláček for his support and feedback.

mation on *when* firms begin automating, (3) the data is from recent years, (4) the firms comprise a panel, and (5) there is a large sample of around 5,000 firms.

The evidence suggests that automation-adopting firms are already larger and more productive, but also benefit significantly once they adopt. The static results suggest automating firms are larger, pay higher wages, and are more productive. Taking a dynamic perspective, I find that these firms have higher growth rates. Finally, I find that firms grow faster once they become automaters.

There is concern that automation will disrupt labour markets, replacing the work of many across a variety of industries and occupations (Susskind and Susskind, 2015). It seems that this has already happened in some contexts, with the most widely-studied automation technology to date: robots. There is growing evidence that, on aggregate, the adoption of robots has led to a fall in total employment (Acemoglu and Restrepo, 2020; Chiacchio, Petropoulos and Pichler, 2018; Carbonero, Ernst and Weber, 2020). How can we reconcile this with my findings that firms using automation technologies get larger after adoption? I take a standard firm dynamics model and introduce two simple extensions: (1) firms hire routine and non-routine labour, with adjustment costs, and (2) firms can invest in automation technology which can perform the tasks of routine workers. The model replicates many of my empirical findings, and crucially it shows that while automating firms may grow, aggregate employment can shrink. It is the equilibrium effect that is crucial: automating firms expand, prices fall, and low-productivity firms exit.

The model allows me to highlight the effects of automation with heterogeneous firms. It can be used to understand what automation among incumbents means for competition, aggregate productivity, the rate at which startups enter and at which firms shut down.

As highlighted in Seamans and Raj (2018), economists "lack an understanding about how and when robotics and AI contribute to firm-level productivity, the conditions under which robotics and AI complement or substitute for labor, how these technologies affect new firm formation, and how they shape regional economies." This has been primarily due to a lack of available data on technological adoption at the firm level.

A number of recent studies have attempted to respond to this problem, utilising firm-level automation data from the USA (Dinlersoz and Wolf, 2018), Denmark (Kromann and Sorensen, 2019; Humlum, 2019), Germany (Benmelech and Zator, 2022), China (Cheng et al., 2019), Spain (Koch, Manuylov and Smolka, 2019), Canada (Dixon, Hong and Wu, 2020), and the EU (Jager et al., 2015). However each study has its limitations, either the time period of analysis, the variety of automation technologies, or a small sample of firms.

The closest empirical paper to this is Zolas et al. (2020), which investigates U.S. firms and finds that adopters of advanced technologies tend to be larger and older. Furthermore, they show that while digitisation (such as Cloud Computing) is quite widespread, the adoption of more advanced technologies (such as Artificial Intelligence) is rare. Finally, they find a hierarchy of technological adoption, such that firms using the more advanced technologies also tend to use the more commonly adopted innovations. The results in this paper align with the majority of their findings.

I use the Bank of Italy's "Survey of Industrial and Service Firms" firm-level automation data to investigate the relationship between automation, productivity, firm dynamics and employment. This survey has been conducted over a long time, for a large sample of firms, asking a wide range of automation-related questions, including recent questions on "Industry 4.0". For example, it asks about the use of Artificial Intelligence (AI), the Internet of Things (IoT), and Industrial Robotics. This survey has approximately 5,000 firms in the panel, and has been run from 1984 to the present. It is an excellent dataset to examine which firms automate, how this has changed over time, and the impact of these choices.

My results are consistent with this nascent field of research on firm-level adoption of automation technologies. For example, firms that automate tend to be larger (Benmelech and Zator, 2022; Bartelsman, Van Leeuwen and Nieuwenhuijsen, 1998; Koch, Manuylov and Smolka, 2019; Cheng et al., 2019; Acemoglu, Lelarge and Restrepo, 2020; Dixon, Hong and Wu, 2020). Likewise, I find that such firms are 2 - 6% larger, even when accounting for firm age, sector, and region. I also find that firms that automate are more productive, with estimated TFP around 3% higher. Other studies have also found this positive relationship between automation and productivity, although often focusing only on robots or manufacturing (Dinlersoz and Wolf, 2018; Kromann and Sorensen, 2019; Benmelech and Zator, 2022; Bartelsman, Van Leeuwen and Nieuwenhuijsen, 1998; Kwon and Stoneman, 1995; Koch, Manuylov and Smolka, 2019).

I find that technology adopters grow faster than non-adopters, but there is little evidence of this difference for blue-collar employment. This suggests that some workers benefit from these technologies, but it varies across different skills and industries (Dixon, Hong and Wu, 2020; Kariel, 2021; Dauth et al., 2021). By focusing on the impact *on adoption*, I continue to find significant overall employment effects, suggesting the contribution of selection effects is muted. Again, there seems to be a limited impact on unskilled workers and productivity (apart for firms using robotics). In order to fully understand what happens to firms on adoption of technologies, I conduct event studies which show a considerable boost in employment from automation technologies, in the range of 4 - 11% five years after adoption.

A model of automation is introduced, extending the Hopenhayn (1992) framework. This is a workhorse model of industry dynamics which lends itself to questions about the size distribution of firms, entry and exit behaviours, and the impact of policies (e.g. a robot tax). Automation is built into the production function through a task-based framework (Acemoglu and Restrepo, 2018*b*), where such technology can displace routine workers, but complements non-routine labour. The calibrated model produces predictions about the effect of automation, and can then be compared to the data.

A recent paper from Hubmer and Restrepo (2021) similarly embeds automation in a standard firm dynamics model, with a fixed cost to automation, to investigate long-run shifts in the U.S. labour share and the role of endogenous markups to study reallocation. They find that substitution of labour for machines has played an important role in the falling manufacturing labour share.

The paper is organised as follows. Section I introduces the data, presents results on firm dynamics, and summarises findings on automation adoption and investment. Section II focuses on the firms that automate. I investigate their growth and productivity rates, and look at the causal impact of adopting automation technologies. The model is described in Section III, along with the calibration and results.

I. Data

The data comes from a survey of Italian firms, which I describe in this section. The reason for using this survey is threefold: it samples a large number of representative firms; most firms stay in the survey allowing for panel analysis; questions on automation technology adoption are asked regularly.

This section introduces the data and summarises the findings on automation adoption. I present new evidence on technology adoption and investment across firm distributions. A consistent finding is that adopters of automation technologies tend to be larger, but do not systematically vary by age.

A. *Bank of Italy Survey*

The data is from the Bank of Italy "Survey of Industrial and Service Firms" (Banca d'Italia, 2021). This survey asks a wide range of questions from a representative sample of around 5,000 firms with at least 20 employees. From 2001 and 2002 respectively, the survey has included smaller businesses and services firms, to better represent the Italian firm population. Firms in the survey are always contacted to be included in the next year, but may not be included in the sample if they switch sector or fall below the threshold size.

The survey uses a one-stage stratified sample design. The strata are selected according to sector, size (average annual number of employees), and region of head office. Firm-year weights are computed with Horvitz-Thompson estimators, and post-stratification adjusted weights are computed using outside information of certain geographic characteristics. Further details on the survey design can be found in Appendix A.

The survey collects annual data on firm employment, investment, turnover, and other structural information. It also has further detail on specific issues, which may not be asked annually, such as strategies, governance, and technological factors. Firms were asked questions on automation technologies from 2015 - 2019. In odd years, they are asked about the use of distinct technologies which have the potential to replace labour inputs across some tasks. Firms give a binary response on the current use of each technology, alongside the number of years since adoption (in 2015 and 2017). These technologies are: Cloud Computing, Artificial Intelligence (AI), Big Data, the Internet of Things (IoT), Industrial Robotics, and 3D Printing. From 2016 - 2019, firms are asked the share of total investment which was spent on advanced digital technologies.

Information on the adoption of various technologies was collected in 2015, 2017, and 2019, with approximately 3,400, 3,800, and 2,100 firms responding in each year, respectively.[1] The number of firms adopting each technology in each year can be found in Appendix C.

B. *Automation Technologies*

Firms using automation technologies are larger, but adoption is less strongly associated with age. Firm technology adoption varies across the technologies, both in terms of sectors (e.g. Robotics is more common in manufacturing, while Cloud Computing is adopted in services) and firm characteristics (such as age and size). I estimate firm-level productivity differences between automaters and non-automaters, finding that firms using these technologies are more productive.

Automation technologies are adopted by around one third of firms, but these businesses employ a significantly larger proportion of workers. The most-used advanced technology is Cloud Computing (21% of firms in 2017, and 28% in 2019). The other technologies are adopted by a smaller share of firms: the Internet of Things (13 - 16%), 3D Printing (5 - 11%), Industrial Robots (7 - 15%), AI and Big Data (9 - 13%).

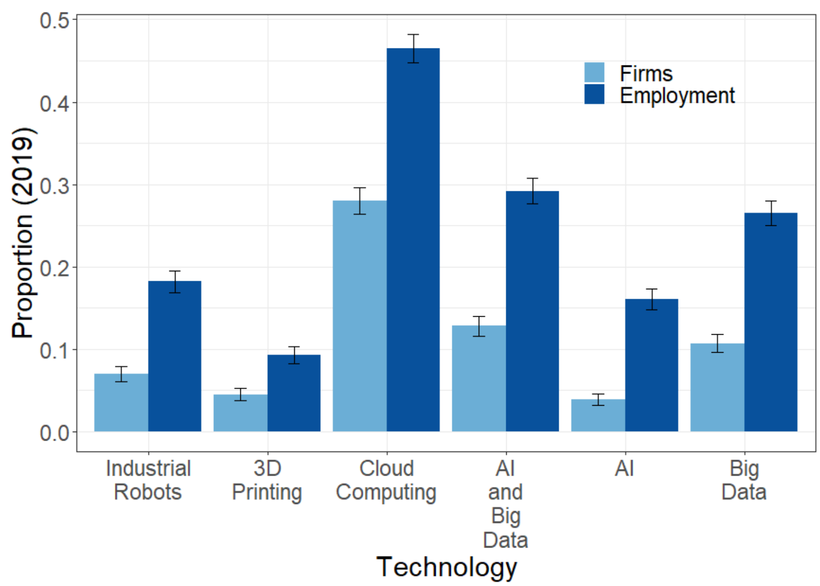
Overall, firms adopting *any* of these automation technologies take up a much larger share of employment: in 2015, 30% are adopters, employing 43% of workers. This rises to 33% of firms and 51% of employees in 2017, followed by 37% of businesses and 56% of labour in 2019. The graphs in Figure 1 split this relationship by each technology in 2019. The light blue bars show the share of firms adopting each technology, while the dark blue bars plot the share of employment in adopting businesses. Clearly the employment shares exceed the firm shares, generally by a factor of between two and three.

As an example, firms using AI & Big Data employ almost 63 workers on average in 2015, compared to just under 49 for non-adopters. Furthermore, despite being larger, firms using this automation technology also paid more *per* worker: such firms renumerated workers with over €31,000, compared to under €29,000 for businesses not using this technology.

The adoption of automation technologies varies widely across industries. The 'Digital' technologies (Cloud Computing, AI, Big Data, Internet of Things) are most common in Transport & Communication, Real Estate, and Wholesale & Retail. For example, Cloud Computing is most commonly found in Real Estate businesses, having been adopted by almost a third of firms in 2017. Within 'Digital' tools, there are significant sectoral differences: the Internet of Things is heavily adopted in Metal Manufacturing but not Hospitality, while this adoption pattern is somewhat reversed for the other three technologies. It is not surprising that 'Physical' technologies (Industrial Robotics and 3D Printing) are concentrated in Manufacturing. For example, Robotics are adopted in over 20% of firms in Metal Manufacturing, and over 10% of businesses in Chemicals, Rubber

[1] The decline in the 2019 sample is attributed to the COVID-19 pandemic. Data is collected for 2019 at the start of the following year, from January to May 2020. The Bank of Italy reports that the response rate did not vary systematically across sectors, firm size classes, and regions. See `https://www.bancaditalia.it/pubblicazioni/indagine-imprese/2019-indagine-imprese/en_statistiche_IIS_01072020.pdf?language_id=1`.

Figure 1. : Technology Adopters: Proportion of Firms and Employment



& Plastics. Robots are least commonly found in Services (Hotels, Restaurants, Wholesale, Retail). Similar numbers are obtained for adoption of 3D Printing. All sectoral results can be found in Appendix B.

Regressions of technology adoption on log employment and age show that employment is always strongly positively associated, while age is not. The estimated coefficients on log employment range from 0.03 - 0.08, and are always significant at the 1% level or below (see Tables C1 to C3 in the Appendix). Thus a percentage rise in employment raises the likelihood of adoption in the 3 - 8% range. These estimated coefficients barely change with the inclusion of firm age, which is, generally, small and insignificant. It is only for AI & Big Data (negatively) and Industrial Robotics (positively) that there is evidence age is associated with adoption of technology.

Firms that automate tend to adopt more than one of these advanced technologies (see Tables C4 and C5 in the Appendix). Firms adopting AI overwhelmingly use Big Data in 2017 (90%). These two technologies go hand-in-hand; the benefits of AI and Big Data depend significantly on use of the other. Likewise, there is significant adoption of both of the more industrial technologies: Robots and 3D Printing (84% and 86% in 2015 and 2017). This suggests a distinction between firms that automate, by adopting *any* of these technologies, and those that do not.

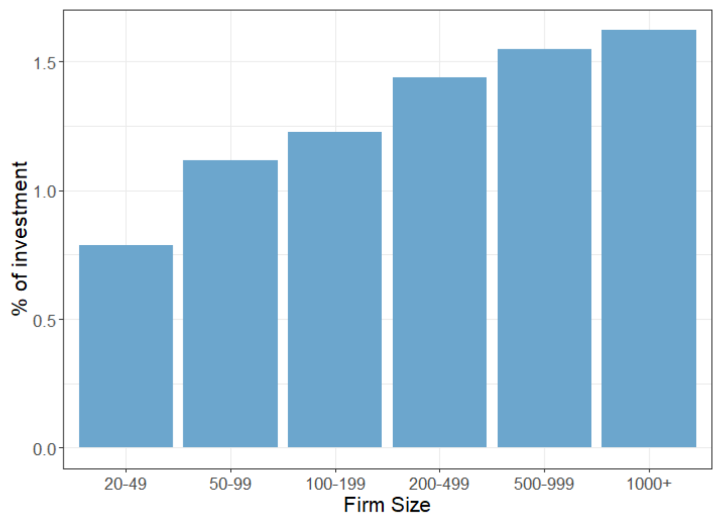
I find that adoption of automation technologies is reversible. A non-negligible proportion of firms that use advanced technologies in time t no longer use them in time $t+h$. Figure B17 in the Appendix highlights this result. For example, around 15% of firms that use AI & Big Data *at some point* between 2015 and 2019 go from ‘adopter’ to ‘non-adopter’ in that time frame. A similar share go in the other direction, while less than 3%

use this technology throughout.[2]

C. Automation Investment

The share of total investment allocated to advanced technologies increases systematically with size, but not unconditionally with age. Figure 2 highlights the size relationship. Firms with under 50 employees allocate less than 0.8% of total investment towards automation technologies, while the share is over twice that for large businesses with over 1000 workers. Further graphs on automation investment shares in Appendix C.

Figure 2. : Investment Share on Advanced Technology Rises with Firm Size.



Note: Each bar shows the average share of investment spent on advanced technologies in each size bucket, averaged over 2016 - 2019.

I regress the share of investment in advanced technology on firm size and age, with sector and region fixed-effects, in each year 2016 - 2019 separately. The results are contained in Table C18 in the Appendix.

The results highlight that larger firms invest a greater proportion in these technologies. Across each year, the estimated coefficient on firm size is large in magnitude and statistically significant, while age is not. Larger firms invest a greater share in automation technology, even controlling for age, sector, and region, with an increase of 0.25 - 0.30% for each percentage rise in employment.[3]

[2]It is possible that this finding is partially affected by measurement error. If different respondents fill in the survey, and are not fully aware of technology adoption within the company, I could spuriously count this as 'dropping' a technology.

[3]The regression specification of $Y = \beta \ln X + \varepsilon$ gives $\beta = \frac{dY}{\%\Delta X}$ which, in this case, is the change in the share of investment in advanced technologies with a percentage change in employment.

II. Empirical Findings

This section focuses on automating firms, investigating their productivity and growth rates, relative to firms that do not automate. I show that firms that automate have productivity around 3% higher than non-adopters, although there is variation across the technologies. It is also the case that automating firms grow at faster rates, in the range of 0.6%.

These findings help build a picture of firm behaviour with regards to automation, and inform the model. However, they also present challenges in interpreting the causal relationship: does automation boost firm size, or are larger firms more able and willing to invest in such technologies? I use three approaches to answer this question: propensity score matching, two-way fixed effects models, and event studies. Each method provides strong evidence that automating firms grow faster than non-adopters. Put simply, firms that automate grow faster *when* they do so.

A. Productivity of Automating Firms

The relationship between productivity and technology use is an important question to examine. Both the correlation and the direction of causality can be informative about firm behaviour. To estimate firm-level productivity, I follow the literature on control function estimation (Olley and Pakes, 1996). Information on the method used to compute the firm-level capital stock is in Appendix D. I find that firms that adopt automation technologies are more productive than those that do not.

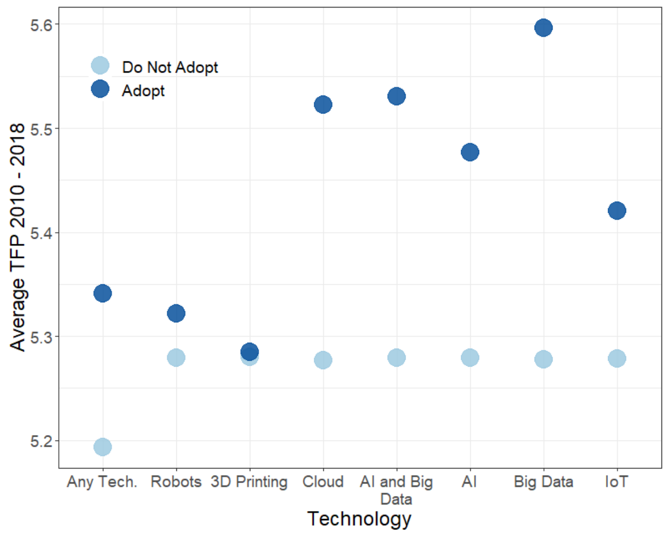
The results for estimated TFP across firms that do and don't adopt automation technologies are shown in Figure 3. For firms adopting *any* technology, they are around 3% more productive than firms which do not, on average. For the 'Physical' automation technologies - Robotics and 3D Printing - adopters are only slightly more productive, at under 1% and 0.1% respectively. The productivity of firms using 'Digital' technologies such as Artificial Intelligence is much higher, relative to non-adopters: it sits between 2.7 - 6.1%.

B. Automation & Firm Growth

I leverage the panel to label firms as technology adopters, and non-adopters, from 2010 - 2018. Firms that use advanced technologies grow consistently faster than those that do not, as seen in Table C20 in the Appendix. The difference in growth rates for adopters and non-adopters is compared across firm size and age distributions. I find that the average growth rates of automating firms are higher than that of non-adopters, across the age distribution (see Figure B23 in the Appendix). This finding also holds across the size distribution for small- and medium-sized firms (Figure B24 in the Appendix) and when I separate results across technologies (Figure B25 in the Appendix).

To get a sense of the magnitude of these growth differences, I regress firm growth on size, age, year, and an indicator for whether the firm ever adopts *any* automation technology, from 2010 - 2018. The resulting estimated coefficient represents the extra

Figure 3. : Adopters have higher TFP than Non-Adopters, 2010 - 2018



Note: Each point shows the employment-weighted average estimated TFP for firms that do or do not automate, over the time period 2010 - 2018. The TFP estimation procedure follows standard control function approaches.

growth associated with the adoption of automation technology. Table 1 contains the results that indicate firm growth is around 0.6 - 0.7% higher for automating firms. Given that the difference in growth rates for *all* firms with 1000+ employees compared to those with 20 - 49 is around 3% (see Table C17), it is clear that automation technology is associated with significantly higher firm growth, akin to being a substantially larger firm.

Table 1—: Estimates of technology adoption coefficient from firm growth regressions.

Coefficient	0.0068^{**}	0.0065^{**}	0.0065^{**}	0.0062^{**}
SE	(0.0031)	(0.0031)	(0.0031)	(0.0031)
Age		✓		✓
Year			✓	✓
N	25,093	25,076	25,093	25,073

Note: Robust standard errors clustered at firm level. Coefficients labelled by statistical significance at: *** 1%, ** 5%, * 10%.

C. What Happens When Firms Automate?

It is clear that automation is more common in larger firms, and that they grow faster. Therefore, identifying the *impact* of automation on firm size is tricky, as we face an endogeneity problem: the sample of firms using advanced technologies seem fundamentally different pre-adoption to those that never adopt.

MATCHING AUTOMATERS AND NON-AUTOMATERS. — The first method to account for this problem is propensity-score matching (PSM). Propensity scores for the probability of adopting automation technology are computed using a logit with a wide range of potentially useful explanatory variables (age, turnover, investment, exporting behaviour, wage, hires per worker, fires per worker, blue-collar proportion of workers, alongside sector and region fixed-effects). Then various methods can be used to 'match' automation adopters to non-adopters, based on the propensity scores. I use the 'matched' set of firms to compare those using technologies to similar non-adopters. I regress log of firm employment on technology adoption for these matched sets. This provides evidence that technology adopters are significantly larger than similar non-adopters, as seen in Table 2.

Table 2—: Propensity Score Matching Regression Results, 2015

	Dependent variable: *Log Employment*					
	Any Tech.	*Cloud*	*AI & Big Data*	*IoT*	*Robotics*	*3D Printing*
Tech. Adoption (nearest)	0.461***	0.822***	0.623***	0.475***	0.370***	0.330**
	(0.06)	(0.07)	(0.11)	(0.08)	(0.10)	(0.11)
N	1914	1376	674	1042	720	524
Tech. Adoption (full)	0.586***	0.400***	0.818***	0.583***	0.535***	0.537***
	(0.05)	(0.06)	(0.07)	(0.06)	(0.07)	(0.08)
N	2554	2580	2547	2541	2544	2538
Tech. Adoption (optimal)	0.493***	0.046	0.823***	0.680***	0.648***	0.606***
	(0.06)	(0.06)	(0.11)	(0.08)	(0.09)	(0.11)
N	1914	1376	674	1042	720	524

*Note: Estimates are significant at levels of 0.1%: ***, 1%: **, 5% *. Coefficients are for log employment regressed on (binary) technology adoption, with matching described in brackets: "nearest" performs greedy nearest neighbour matching; "full" performs optimal full matching, so treated and control observations are assigned to a class and each receives at least one a match; "optimal" is similar to "nearest", but aims to minimise the mean of the absolute pair distances in the matched sample.*

FIXED EFFECTS. — I leverage the large set of firms over the panel to analyse the relationship between technology adoption and firm size. There are around 3,500 firms that can be labelled as adopters or non-adopters of advanced technologies. Compiling a panel of these firms over the period 2010 - 2018 gives around 25,000 firm-year observations. I investigate how technology adopters differ over time, and how firms change before and after adoption.[4]

I employ two-way fixed-effects (TWFE) models, to estimate the difference in firm outcomes between adopters and non-adopters. This model has unobserved individual- and time-specific effects, which is important in this context. Firstly, some firms may be inherently more productive and have greater growth potential, for a host of unobservable reasons such as aggregate conditions at entry (Sedláček and Sterk, 2017), ex-ante heterogeneity (Sterk, Sedláček and Pugsley, 2021), or managerial practices (Bloom, Sadun and Reenen, 2016). Secondly, firm outcomes are likely to be tightly linked to the prevailing aggregate conditions of the macroeconomy and labour market.

However, the TWFE model relies on the underlying assumption of linear additivity of the two unobserved confounders. Crucially, this leads to 'treated' units being compared to observations described as 'mismatches' in the literature (Imai and Kim, 2019). The intuition here is that we *should* be evaluating the causal treatment effect by comparing each 'treated' firm to an average of control units from the same firm (within-unit), plus the average of control firms from the same year (within-time), adjusting for the average outcome across these two control groups. However, in constructing these control sets, we may match a firm to one with the same treatment status (e.g. has also adopted automation technology). Imai and Kim (2019) show it is impossible to avoid this issue, even with a weighted TWFE estimator which attempts to eliminate mismatches in the within-unit and within-time sets.

Therefore, I will also employ an event study design to show how firm outcomes change before and after adoption. This further allows me to look at the differential effects of adopting automation technology over time, and permits testing of selection by observing pre-trends. The results from the TWFE models and event studies both show broadly the same results, both in direction, and magnitude.

The TWFE model is deployed to investigate the difference in employment, blue-collar employment, and labour productivity (proxied by turnover per worker) between firms that do and do not automate. These variables are regressed on firm and time fixed-effects, along with a control for firm age, and the variable of interest: a binary technology adoption variable (i.e. does firm i ever adopt the technology?).

$$\ln Y_{it} = \mu_i + \gamma_t + \delta X_{it} + \beta \mathbb{1}\text{Tech}_{it} + \varepsilon_{it} \tag{1}$$

The set of β are shown in Table 3.

The results in Table 3 provide evidence that firm size rises upon adoption of each of these advanced technologies, in the range of 2 - 6 %. Although the point estimates for the effect of adoption on blue-collar employment are negative for Cloud Computing, AI & Big Data, and 3D Printing, the standard errors are large enough for the latter two

[4]Given that there is potentially non-random non-response to the questions on automation adoption, I use the class non-response adjustment factor to re-weight my panel as in Dargatz and Hill (1996).

Table 3—: Estimated β from homogeneous effect TWFE model: the % change in variables when adopting technology, relative to non-adopters.

		Cloud	*AI & Big Data*	*IoT*	*Robotics*	*3D Printing*
Employment	Coeff	0.020***	0.052***	0.051***	0.042***	0.056***
	SE	(0.0043)	(0.0061)	(0.0048)	(0.0062)	(0.0066)
Blue-collar Emp.	Coeff	−0.036*	−0.030	0.0008	0.048	−0.025
	SE	(0.015)	(0.027)	(0.021)	(0.027)	(0.028)
Turnover per worker	Coeff	0.0057	−0.017	0.017*	0.065***	0.019
	SE	(0.0066)	(0.0096)	(0.0075)	(0.0097)	(0.010)

Note: Robust standard errors clustered at firm level. Coefficients labelled by statistical significance at: *** 0.1%, ** 1%, * 5%.

that I cannot interpret these as statistically significant. Likewise, there is little evidence that using these advanced technologies raises turnover per worker, apart for Industrial Robotics and IoT. For robots, the estimate is large (at 6.5%) and statistically significant. The result for IoT is smaller (at 1.7%) and only holds at a 5% level of significance.

EVENT STUDIES. — Knowledge of *when* firms adopt technologies also permits an event study specification in which the firm outcomes are regressed on a set of dummy variables which indicate the time relative to adoption year. The specification takes the form:

$$\ln Y_{it} = \mu_i + \gamma_t + \delta X_{it} + \sum_{j=\underline{j}, j\neq -1}^{\bar{j}} \beta_j \mathbb{1}(D_{it} = j) + \varepsilon_{it}$$

where $D_{it} = t - A_i$ is the 'relative time', or the number of periods relative to when firm i adopted technology in year A_i (Borusyak, Jaravel and Spiess, 2021). The outcomes of interest Y_{it} are employment, hours, wages, and turnover of firm i in year t. The regression includes both firm and year fixed effects. The time-invariant controls are sector and region, and the time-varying control is firm age.

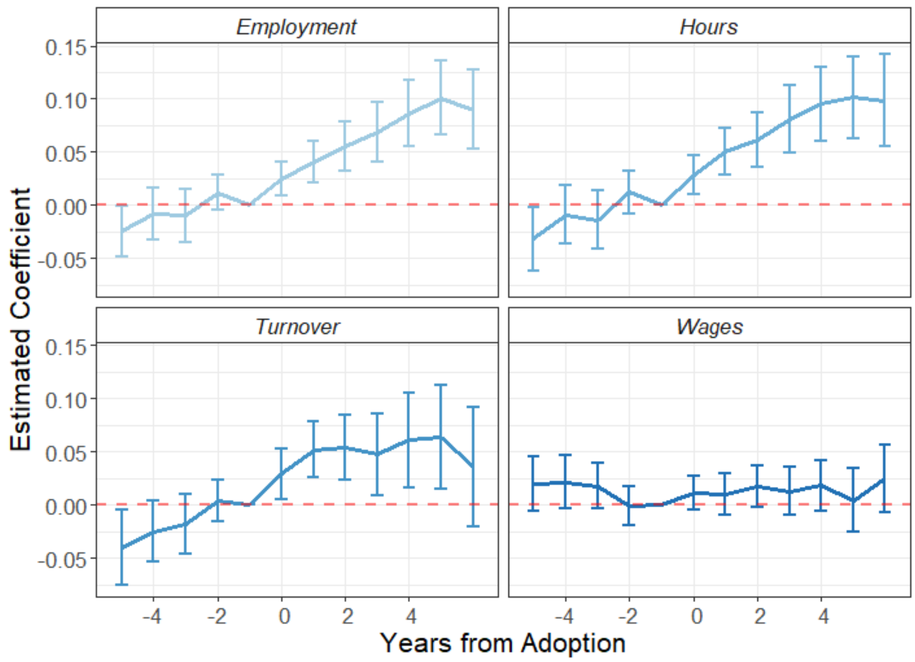
I find some evidence of pre-trends from this event study specification. Results from this exercise are presented in Figures B19 and B20 of the Appendix. Where these pre-adoption estimates are negative and statistically significant, this is suggestive that there is a general pre-adoption trend in firm outcomes. The linear pre-trends in log employment, log hours, log wages and log turnover[5] are noticeable, especially for Industrial Robotics and 3D Printing.

Therefore, I follow Borusyak, Jaravel and Spiess (2021) and deal with this by iden-

[5]I actually use the Inverse Hyperbolic Sine (IHS) transformation (Bellemare and Wichman, 2020) for turnover, rather than log, due to a small number of zeros in the data. But unlike log, the IHS approximation is defined at zero, and the coefficients can be interpreted analogously.

tifying the deviation from a linear pre-trend. This is done by dropping two 'reference' periods, rather than just one. I drop the earliest period (6 years before adoption) and continue to exclude the period prior to adoption. The results for Artificial Intelligence and Big Data are presented in Figure 4. I focus on one technology for ease of exposition. For all technologies, the results can be found in Figures B21 and B22 in the Appendix. Although the linear pre-trends are still somewhat apparent, they are shrunk towards zero and mostly not statistically significant.

Figure 4. : Estimates from Event Study Regression on AI and Big Data



Note: Regression with 3,270 firms and 24,544 firm-year observations. Standard errors clustered at the firm level.

The results from the event studies highlight a clear sustained rise in employment in the years following adoption of these automation technologies, both at the extensive and intensive margins. There is evidence that turnover also rises on adoption, but not for Cloud Computing, nor AI & Big Data. The results for wages have much larger standard errors, showing no clear pattern, and no statistically significant effects across all technologies.

The boost to employment seems most pronounced for AI & Big Data, 3D Printing, and the Internet of Things. This is consistent with the previous results which considered the impact of adopting automation technologies using TWFE models.

More specifically, most of the point estimates prior to the reference year are insignificant across all technologies, apart from 5 years prior to adoption in some cases. This arises from the issue of linear pre-trends, as previously discussed. There is some mild evidence of a pre-trend in employment for adopters of 3D Printing. Overall I am reasonably confident that the event study identifies how firm outcomes change with technology adoption. However, the existence of a pre-trend implies that my post-adoption point estimates for 3D Printing are biased *downwards*. The interpretation of such pre-trends is that adopters of 3D Printing grow more slowly than non-adopters *prior to adoption*. Thus, the impact of investing in 3D Printing would actually be larger than my results suggest.

The results show a statistically significant relationship between technology adoption and firm size, in the range of 1 - 3 % in the first two years post-adoption, and rising to 4 - 11% in the final two years of the sample. These effects are statistically significant across all technologies, and the magnitudes are not trivial. Furthermore, these results hold at the intensive margin, with a rise in hours of 2 - 4 % in the first two years, which increases to 4 - 12 % in the fifth and sixth years post-adoption. Overall, the employment effects are most muted - but still positive - for Mobile & Cloud Computing.

It seems that firms using automation technologies also experience a large and significant rise in turnover: in the first two years, there are increases of 2 - 8 %, with smaller gains for firms adopting the Digital technologies (Cloud, AI etc.) and bigger returns for those using Physical technologies (Robots and 3D Printers). After five years, the effect on turnover is in the range of 8 - 12 % for IoT and Physical technologies. The medium-run effect for AI & Big Data is around 6%, and although there are large standard errors, the estimated effect is still generally positive. However, for Mobile & Cloud Computing, the estimated effect on turnover is not distinguishable from zero.

Finally, firms' average wage doesn't seem to change significantly after implementing automation technologies. For Physical technologies, it seems that adopters' wages have essentially no pre-trend - coefficients are close to zero and insignificant - but the point estimates *are* positive after adoption. Sometimes these are statistically significant, especially for firms using 3D Printing technology. Overall, though, the evidence is not especially strong that automating firms' wages rise after adoption. This may not be entirely surprising: firms may grow through using new technologies, but the average wage will only grow to the extent the composition of workers adjusts. If firms that start using Machine Learning algorithms already had a higher-than-average share of skilled technical employees, and expand by continuing to hire in that ratio, the average wage may not rise.

D. *Empirical Takeaways*

I have highlighted important novel findings on firms that automate. Firstly, I find that firms adopting automation technologies are already larger and grow faster than non-adopters. Secondly, firms grow even faster *after* they adopt these technologies. Taken together, it seems that automation increases 'inequality' across firms. This could have important consequences for competition among firms, such as increased up-or-out dynamics, rising market power, or 'superstar firm' effects.

These facts motivate further investigation with a model, to help understand the effects of automation on firm dynamics and macroeconomic outcomes.

III. Model

I introduce a model of heterogeneous firms that can endogenously choose to automate. The aim of this model is twofold. Firstly, it allows me to analyse the impact of automation when firms differ and have the option to automate tasks, taking into account the trade-off between marginal and fixed costs from new technologies (De Ridder, 2019; Lashkari, Bauer and Boussard, 2019). Automation lowers marginal costs, making firms more productive, but there is a selection effect, as only *more productive firms* can afford the associated fixed costs. The impact on overall productivity is ex-ante unclear, and depends on both selection and reallocation. The effect on employment is also not obvious, as it depends on which firms expand, contract, enter, and exit. Secondly, I am interested in the partial equilibrium effects. Automation influences the equilibrium price by affecting input costs. This will impact firm entry and exit. Furthermore, changes in demand for labour caused by automation technologies will lead to a shift down the labour supply curve, with wage and employment effects.

I take a standard Hopenhayn (1992) heterogeneous firm dynamics model with adjustment costs on labour. I extend it to include a task-based production function (Zeira, 1998; Acemoglu and Restrepo, 2018*b*), routine and non-routine labour which produce different sets of tasks, and automation technology which can replace routine workers.

A. *Task-based Production Function with Automation*

In the standard Hopenhayn (1992) model, firms are heterogeneous in productivity z and output is determined by one labour input n with decreasing returns to scale. The production function is $y = zn^{\alpha}$.

Taking inspiration from Acemoglu and Restrepo (2018*b*), the new production function depends on productivity and production over a set of tasks x of increasing 'difficulty'. This allows for jobs that are made up of a variety of tasks, which might be performed by different inputs depending on their complexity. Thus firm output is:

$$\ln y = \ln z + \int_0^{\phi} \ln y(x) dx \quad \text{where } \phi < 1 \text{ for DRTS} \tag{2}$$

The production of each task $y(x)$ is determined by the set of tasks which can be performed by different inputs. I assume that routine labour n^r can be perfectly substituted by automation technology R, such as industrial robots, for some set of tasks. However, non-routine labour n^n cannot be substituted for, among the more complex tasks. This is depicted in Figure 5, where $q < w^r$ highlights that, should a firm have access to automation technology, the marginal cost of technology is less than the routine labour wage.

Of course these sets of tasks will change over time, as advanced technology improves.

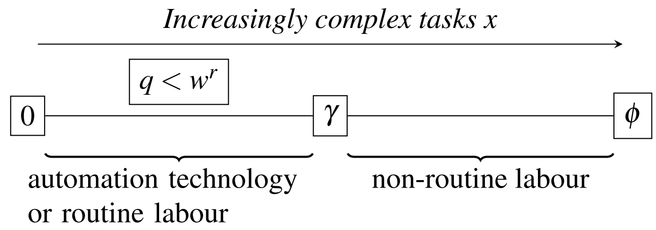


Figure 5. : Structure of Task-Based Production Function

Production of a task is determined:[6]

$$y(x) = \begin{cases} r(x) = R(x) + n^r(x) & \text{for } x \in [0, \gamma) \\ n^n(x) & \text{for } x \in [\gamma, \phi) \end{cases} \tag{3}$$

The prices of inputs are w^n, w^r, q for non-routine labour, routine labour, and automation technology. This price q is the per-unit cost of using the technology, such as the electricity or computing power associated. I assume that $\frac{q}{w_r} < 1$ such that automating is beneficial. However firms must pay a fixed cost c_a in each period to use automation technology R. This can be thought of as the cost of paying a company to maintain the robots, or an annual payment to access cloud computing services. This does not scale with the amount of technology used, as does the technology input cost q. The production function is therefore:

$$\ln y = \ln z + (\phi - \gamma) \ln n^n + \gamma \ln r \tag{4}$$

$$y = z(n^n)^\alpha r^\gamma, \tag{5}$$

where $r = n^r + R$, and $\alpha = \phi - \gamma$. This yields a production function that has capital-skill complementarity, which is an idea going back to at least Griliches (1969).

Heterogeneous Firm Model

Firms produce with decreasing returns to scale and choose inputs n^n, n^r, R to maximise profits (dropping the subscript t for ease of notation):

$$\pi(z, n_{-1}) = pz(n^n)^\alpha (n^r + R)^\gamma - w^n n^n - w^r n^r - qR - g(n, n_{-1}) - c_f \tag{6}$$

where $n = n^n + n^r$ is the total labour input, n_{-1} is the previous period choice of labour

[6]Choosing to split labour inputs into routine and non-routine is inspired by a rich literature on the substitutability of automation-related technologies with labour inputs. For example, Jaimovich and Siu (2012) look at the changes in employment shares by occupation group in the US, and find this distinction to be important.

inputs and $g(.,.)$ is an adjustment cost function. Firms differ in productivity z, which follows AR(1) process:

$$\ln z_{t+1} = \ln \bar{z} + \rho \ln z_t + \sigma_z \tag{7}$$

The value function of a firm is the largest of the 'automating' and 'non-automating' value functions, taking into account the fixed automation cost c_a. These value functions, and the overall value function, are expressed below:

(8)
$$v_t^a(z_t, n_{t-1}) = \max_{R_t, n_t^n, n_t^r \geq 0} \left\{ \pi(z, n_{-1}) + \beta \max \left\{ \int v_{t+1}(z_{t+1}, n_t) dF(z_{t+1}|z_t), -g(0, n_t) \right\} \right\}$$

(9)
$$v_t(z_t, n_{t-1}) = \max_{n_t^r, n_t^n \geq 0, R=0} \left\{ \pi(z, n_{-1}) + \beta \max \left\{ \int v_{t+1}^a(z_{t+1}, n_t) dF(z_{t+1}|z_t), -g(0, n_t) \right\} \right\}$$

$$\tilde{v}(z_t, n_{t-1}) = \max \left\{ v_t^a(z_t, n_{t-1}) - c_a, v_t(z_t, n_{t-1}) \right\} \tag{10}$$

As in Hopenhayn (1992), there is a cut-off level of productivity z^* such that all firms with $z \geq z^*$ do not exit. Furthermore, there will be a cut-off level of productivity z^a such that all firms with $z \geq z^a$ will automate. The equilibrium price is pinned down by the free-entry condition:

$$v^e(z) = \int_z v(z) dG(z) = c_e \tag{11}$$

Finally the law of motion for the distribution of firms can be computed:

$$\mu_{t+1}(z') = \underbrace{\int_{z \geq z^*} \mu_t(z) dF(z'|z)}_{\text{Surviving incumbents}} + \underbrace{MG(z')}_{\text{Entrants}} \tag{12}$$

where $\mu_t(z)$ is the mass of firms with productivity z at time t, $M > 0$ is a constant mass of potential entrants, and $G(z)$ is the productivity distribution for entrants, which is simply the stationary distribution of the AR(1) process. I solve for M in stationary equilibrium by exploiting the linearity of $\mu_t(z)$, as in Hopenhayn (1992). Effectively, the mass of entrants is chosen so that equation (12) holds, and there is no (net) entry nor exit.

To close the model, I assume downwards-sloping demand for final output $D(p) = \frac{\bar{D}}{p}$, where $\bar{D} > 0$ is exogenous. Price is endogenous, and satisfies the free-entry condition in equation (11). In equilibrium, output is equal to demand, so $Y = \int y(z) \mu(z) dF(z) =$

$D(p)$. This equilibrium condition shows that adjusting $\bar{D}$ simply scales the values of all equilibrium objects up or down. $\bar{D}$ is chosen to clear the labour market. The labour supply curve is upwards-sloping with Frisch elasticity λ, following Clementi and Palazzo (2016): $L^s(w^n) = (w^n)^\lambda$, where w^n is the non-routine labour wage (and the routine labour wage is set as the numeraire).[7]

This model is partial equilibrium, so the labour market is not endogenised from optimisation on the household side. However, an upwards-sloping labour supply curve allows variation in labour demand to lead to changes in the equilibrium wage and employment. If instead a Melitz (2003) framework were chosen, where labour supply is fixed, any changes to labour demand would not affect aggregate employment. This would limit the model from speaking to aggregate employment effects, as all the adjustment would occur through the wage channel.

To summarise, the equilibrium conditions are as follows,

$$D(p) = \frac{\bar{D}}{p}, \quad Y = \int y(z)\mu(z)dF(z), \quad L^s(w^n) = (w^n)^\lambda, \quad L^d = \int n(z)\mu(z)dF(z) \tag{13}$$

B. Solution Method

To solve this problem, I take first-order conditions (FOCs) of the static profit maximisation problem without labour adjustment costs, for firms that automate, and those that do not.[8] The presence of the labour adjustment cost prevents a closed-form solution for optimal input demands, yielding two potential solution approaches. One is to solve these numerically, but this was computationally intensive, which slowed down the calibration process. The second is to approximate lagged employment across a grid,[9] creating a labour cost adjustment matrix for all possible combinations between time periods. A brief outline of the solution algorithm is presented here:

1) Solve optimal input demands across grid of productivity and lagged employment.
2) Use the free-entry condition to find equilibrium price, both with and without the presence of automation technology.
    a) Guess price p_0
    b) Take FOCs of static firm problem to find maximised profit $\pi(p_0; z, n_{-1})$.
    c) Apply value function iteration on this starting point until convergence.

[7]As an example, raising $\bar{D}$ shifts the mass of firms across the productivity distribution up in equal proportion. Labour demand is firm-level demand multiplied by the mass of firms, integrated over the productivity distribution: $\int n(z)\mu(z)dF(z)$. This is clearly impacted by $\bar{D}$, which scales the distribution. In equilibrium, labour demand equates to labour supply, which is the non-routine wage to the power of the Frisch elasticity. Given the calibration sets the non-routine wage at 1.2 times the numeraire routine wage, I choose $\bar{D}$ such that the labour market equilibrium holds in the non-automation calibration. When there are changes to labour demand, for example induced by automation, this will lead to changes in the real wage and employment.

[8]Dropping adjustment costs as a starting point allows for closed-form solutions for the static FOCs, as we ignore the dynamic element of the labour input choice.

[9]I ran the algorithm without automation technology, to give upper and lower bounds for total employment demand.

   d) Compute expected value of entry, and check free-entry condition holds.
   e) Adjust guess of price until free-entry condition holds.

3) Find cutoff productivity level for entry, and for automation.

4) Compute firm choices and distributions.

C. Calibration

The chosen labour adjustment cost function is quadratic, such that $g(n_t, n_{t-1}) = \frac{\tau}{2}(n_t - n_{t-1})^2$ where n_t is the sum of routine and non-routine labour hired in period t. The purpose of this adjustment cost is to better match the data, as justified by long-standing literature (Kydland and Prescott, 1991; Hamermesh, 1989; Cogley and Nason, 1995). The labour adjustment cost is for *total* labour hired: firms can move workers from routine to non-routine tasks, and it is the hiring and firing of workers which incurs a cost.

Table 4—: Model Parameters

	Parameter	**Value**	**Target**
pre-set			
β	Discount rate	0.95	Match annual IR over period
c_e	Entry cost	$0.82 \times c_f$	Barseghyan and DiCecio (2011)
$\frac{w_n}{w_r}$	Wage ratio	1.23	Vannutelli, Scicchitano and Biagetti (2021)
q	Automation price	0.975	By assumption
γ	Routine share	0.66 - α	Residual labour share
ρ	AR1 coefficient	0.8	
σ	AR1 stdev	0.2	
λ	Frisch elasticity	2.0	Clementi and Palazzo (2016)
calibrated			
α	Non-routine share	0.40	Match avg firm size
$\bar{z}$	AR1 intercept	2.06	Match avg labour productivity
c_f	Fixed cost	35.6	Match exit rate in Manaresi (2015)
c_a	Automation cost	6.23	Match % firms that automate
τ	Labour adjustment cost	20.0	Match avg growth rates
$\bar{D}$	Demand scalar	4.16	Clear labour market without automation

The pre-set calibration parameters are fairly standard, or taken from existing literature. From Vannutelli, Scicchitano and Biagetti (2021), the difference in log wage for non-routine to routine workers is 0.21. This implies $\frac{w^n}{w^r} = e^{0.21} = 1.23$. The automation price is set below the routine wage by assumption. This somewhat arbitrary assumption is relatively innocuous; it means at least *some* firms will have an incentive to automate, and I calibrate the fixed automation cost to match the share of firms using the technology. Thus the decision to adopt automation technology is governed by the fixed automation cost, and the automation price is simply set such that some firms automate. It doesn't seem the results are particularly sensitive to this 'automation price'.[10] The calibrated parameters are chosen to target observables which are sensitive to that parameter. The non-routine share is chosen to match the average firm size, as this will determine the labour share in highly productive, automating firms. The AR(1) intercept is chosen to match the average labour productivity, as it determines the level of the productivity distribution from which firms draw. The fixed and automation costs are naturally chosen to match the exit rate and the share of automating firms. The adjustment cost on labour is chosen to match the average growth rate of firms, as this affects the speed of readjustment towards the 'optimal' labour choice.

The calibrated parameters are chosen to find the minimum of the weighted average of the absolute distance between the model and targeted moments, where the weights are the inverse of the targets themselves.[11]

D. Results

I report a set of targeted and non-targeted moments in the model and data in Table 5. The model moments are either steady-state targets, or computed from a simulation of 200,000 firms over 20 periods, where automation is introduced and firms adjust their behaviour over time to this technological change.[12] When necessary, I choose the simulated moments instead of steady-state moments, where I need to track firms that do or do not automate.

Whenever possible, the moments are compared to the data from the Italian firm survey introduced in Section II. However, firms may leave the panel if they become too small, which does not *necessarily* imply firm exit. Hence I use the exit rate in Manaresi (2015) which has the full sample of private Italian firms.

For the non-targeted moments, the routine share of employment of 43% is taken from an Italian study by Vannutelli, Scicchitano and Biagetti (2021), while all other moments from the data are computed from the survey in this paper.

The model fit is good for some moments, but not all. The firms are a bit larger in the model, on average, and grow at a slightly higher rate. The share of firms that automate is a few percent below the data. However, the exit rate is about twice as high as the data, and average labour productivity is much lower than the data (although the units make this a less useful target).

[10]Calibration with other values of q simply leads to different values of c_a to the target share of automated firms, and the other calibrated parameters do not change in any significant way.

[11]Such weights force the algorithm to be 'unit-agnostic', else it would fit larger targets better than smaller ones.

[12]After calibrating the model, I take the resulting parameters and simulate 200,000 firms over 20 time periods. This allows me to introduce automation to the model, and analyse the long-run effects as firms respond: by optimally choosing inputs each period, deciding whether to automate, and exiting the market. I can follow firms over time, identifying if and when they choose to automate, and the resulting impact. I shocks firms' productivity each period following the AR(1) process, and firms choose the optimal inputs on the productivity grid. They automate only if their productivity is equal or greater than z^a, and exit if it is below z^*. If they exit, the firm stays inactive. I do not allow firms to enter for computational ease; this does not change the results which are ratios and time-averages.

The model does well at matching the non-targeted moments. The routine share of employment matches the data very well, while automating firms are slightly larger than the data in terms of employment (48% in model; 42% in data), but about right in output (53% in model; 55% in data). The relative growth rates, relative exit rates, and relative productivity for automating firms have the right sign in the model, but the magnitudes don't match the data.

Relative growth rates of automating firms are high in the model compared to the data. In the simulation, the difference is almost 5 p.p. greater growth for automaters, compared to firms that don't automate. In contrast, this difference is under 1 p.p. in the data. Automating firms exit less frequently than non-automaters in the model, as we see in the data. However, the difference in exit rates is over 17 p.p. in the data, compared to just 9 p.p. in the model. Finally, productivity of automating firms is 19% higher in the model, compared to just 3% in the data.

Table 5—: Model Results

	Model	**Data**
Non-targeted		
Routine share of employment	0.44	0.43[1]
Share of employment in automating firms	0.48	0.42⋆
Share of output in automating firms	0.53	0.55⋆
Difference in growth rates for automating firms (p.p.)	0.047†	0.007⋆
Difference in exit rates for automating firms (p.p.)	-0.089†	-0.176⋆
Relative productivity for automating firms (p.p)	0.19†	0.03⋆
Targeted		
Average firm size	62.3	50.0⋆
Exit rate	0.198	0.098[2]
Average labour productivity	61.79	135.5⋆[3]
% firms that automate	0.27	0.30⋆
Average growth rate	0.021†	0.015⋆

†: moments estimated off long-run averages from firm simulation exercise.
⋆: data from Italian firm panel described in Section II.

[1] Vannutelli, Scicchitano and Biagetti (2021)
[2] Manaresi (2015)
[3] Simply computed as average turnover per worker hour. In 2017, the mean turnover per worker was €221,894. The average weekly hours were 31.5, so over a year we get 1,638. Thus average turnover per worker hour is €135.47.

Another exercise to check the model describes the data well is to calibrate the non-automated model as a starting point. To this end, I set the nonroutine to routine wage ratio at rate consistent with the data 'pre-automation' in the 1980s, at 1.1 (Basso, 2019). Then I back out the labour supplies implied by the model. Automation is introduced the model, and wages are computed to clear the labour market. The nonroutine to routine wage ratio the model gives is 1.285, which is slightly higher than the data, but in the right direction. Overall it seems that this baseline model does a reasonable job of matching the data.

E. What is the Impact of Automation?

I initially solve the model when automation technology unavailable to firms.[13] Then I solve the model with automation, and compare the outcomes. I document the aggregate and firm-level changes when automation technology becomes available in this partial equilibrium framework. Table 6 contains the results.

It is important to underscore that the magnitude of the effects presented here do depend on the elasticities of product demand and labour supply. Automation technology affects firm decisions. Aggregation across firms will shift the aggregate output supply curve and labour demand curve. The extent to which this affects partial equilibrium outcomes depends on the aforementioned elasticities.

Automation technology permits highly-productive firms to grow, and pushes down the equilibrium output price via free-entry, reducing the number of operating firms. A fall in total labour demand leads to a shift down the upwards-sloping labour supply curve, leading to a fall in aggregate employment. The extent of the fall in employment and the real wage depend on the elasticity of labour supply.

Table 6—: Percentage point change relative to 'No Automation' model

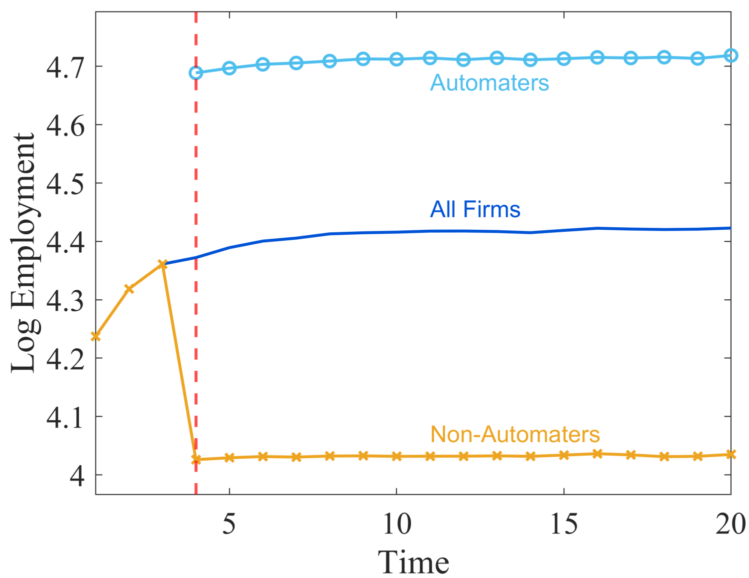
Aggregates:	**Employment**	**-2.49**
	Price	-0.02
	# firms	-8.51
	Output-weighted productivity	+1.34
	Exit rate	+0.10
	Real wage	-1.24
Firm Level:	**Employment per firm**	**+6.58**
	Output per worker	+0.16
	% firms that automate	+27.4

The key result in Table 6 is that automation leads to an aggregate fall in employment, alongside a firm-level rise in employment. These two results have been found in the data, and can be reconciled in this heterogeneous-firm framework.

When cheaper automation technology is available to firms, they purchase this input if they are productive enough. These firms expand due to the low-cost input, and earn significantly greater profits. The equilibrium effect is a lower price, as determined by the free-entry condition. This is because automating firms can produce output more cheaply,

[13]Imagine that initially the per-unit price of automation q_t is greater than that of routine labour, or that automation technology is too undeveloped to produce any tasks that humans perform.

Figure 6. : Average firm-level employment from simulation when automation is introduced.



raising the value of producing output. The lower output price reduces returns to low-productivity firms, so they exit. Overall, the reallocation towards more-productive firms leads to a rise in output-weighted productivity.

At a firm level, the average firm hires more workers and produces more, due to the greater skew of output towards highly productive firms. Firms that automate are larger, as they are able to expand with the new technology. The rise in average firm size over time can be seen in the model simulation in Figure 6, which plots the average firm-level employment once automation technology is introduced.[14]

However, there is a fall in aggregate labour demand (firm-level employment multiplied by the mass of firms). This is due to the fall of the total mass of firms. As labour demand falls, the equilibrium shifts down the upwards-sloping labour supply curve. Thus, the introduction of automation technology in production leads to a fall in aggregate employment and the real wage. The fall in employment is skewed towards routine labour, which takes up a smaller share of total employment.

Figure 6 highlights an important dynamic uncovered in the empirical section. Firms that are already large and productive will invest in automation technology, and grow larger - this is why automaters start much larger than their technologically-lagging counterparts. This also explains why the average size of non-automaters falls: the largest

[14]Automation technology is made available in the fourth period of the simulation, but the dynamics are very similar whenever it is introduced.

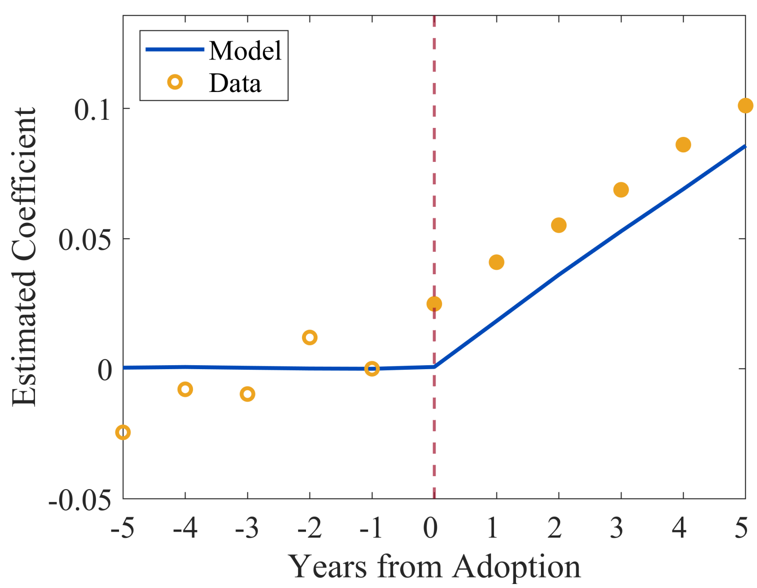
of this group leave, upgrading their technology, which reduces the average size of non-automaters. In sum, the average size of all firms increases, due to the combination of the higher exit rate, and the reallocation of firms between the two groups.

I track firms that automate, before and after automation is introduced, and produce a within-model event study to compare to the data. This is presented in Figure 7, which shows:

- *Data:* event study regression on employment for **adopters of AI & Big Data**, with linearized pre-trends (Borusyak, Jaravel and Spiess, 2021). The filled in points are statistically significant at the 1% level.

- *Model:* log difference in employment for automating firms relative to non-automating firms, normalized to initial difference.

Figure 7. : Model Event Study for Automating Firms



The model reproduces the results from the regression very well. As in the empirical exercise, automating firms are the same size as non-adopters pre-adoption (when controlling for a set of characteristics), but grow faster after implementing automation technologies. That the model accurately produces the shape and magnitude of the event study is promising, as this is an outcome of the mechanisms of the model, and not directly targeted. It is further evidence that the model can account for the findings from the data.

This model can also reconcile the aggregate findings that automation technology reduces aggregate employment (Acemoglu and Restrepo, 2018*a*; Dauth et al., 2021), with my firm-level evidence that automaters grow on adoption. This model highlights the important role for heterogeneity, reallocation, and equilibrium effects.

IV. Conclusion

This paper seeks to understand the adoption of automation technologies among firms, and the equilibrium effects thereof. On the empirical side, I take a novel dataset on firm use of advanced technologies, and I show that automating firms tend to be larger, but also grow faster, both before and after they adopt. The employment growth doesn't show up in blue-collar workers, suggesting that complementarities between automation technologies and skilled workers are strong and important. Furthermore, adopters of new technologies are more productive, but I do not find that productivity is boosted by adoption.

Taking stock of these findings, I extend Hopenhayn (1992)'s seminal heterogeneous firm model to include two types of labour - routine and nonroutine - alongside automation capital which can be substituted for the former. In the model, automation is achieved only by highly productive firms, due to the fixed cost of using this technology. These firms benefit most from automation, allowing them to expand. The equilibrium effect lowers prices, forcing low-productivity firms out of the market. Unsurprisingly, workers lose out significantly, especially those in routine occupations. Importantly, such a model can reconcile the growing evidence that firms grow when they adopt advanced technologies, but the aggregate effect on employment is often negative.

REFERENCES

Acemoglu, Daron, and Pascual Restrepo. 2018*a*. "Artificial Intelligence, Automation and Work." National Bureau of Economic Research Working Paper 24196.

Acemoglu, Daron, and Pascual Restrepo. 2018*b*. "The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment." *American Economic Review*, 108(6): 1488–1542.

Acemoglu, Daron, and Pascual Restrepo. 2020. "Robots and Jobs: Evidence from U.S. Labor Markets." *Journal of Political Economy*, 128(6): 2188–2244.

Acemoglu, Daron, Claire Lelarge, and Pascual Restrepo. 2020. "Competing with Robots: Firm-Level Evidence from France." *ASSA 2020 Papers and Proceedings*.

Atalay, Enghin, Phai Phongthiengtham, Sebastian Sotelo, and Daniel Tannenbaum. 2018. "New technologies and the labor market." *Journal of Monetary Economics*, 97: 48–67.

Banca d'Italia. 2021. "Survey of Industrial and Service Firms."

Barseghyan, Levon, and Riccardo DiCecio. 2011. "Entry costs, industry structure, and cross-country income and TFP differences." *Journal of Economic Theory*, 146(5): 1828–1851.

Bartel, Ann, Casey Ichniowski, and Kathryn Shaw. 2007. "How Does Information Technology Affect Productivity? Plant-Level Comparisons of Product Innovation, Process Improvement, and Worker Skills." *The Quarterly Journal of Economics*, 122(4): 1721–1758.

Bartelsman, Eric, George Van Leeuwen, and Henry Nieuwenhuijsen. 1998. "Adoption Of Advanced Manufacturing Technology And Firm Performance In The Netherlands." *Economics of Innovation and New Technology*, 6(4): 291–312.

Basso, Gaetano. 2019. "The evolution of the occupational structure in Italy in the last decade." Bank of Italy, Economic Research and International Relations Area Questioni di Economia e Finanza (Occasional Papers) 478.

Bellemare, Marc F., and Casey J. Wichman. 2020. "Elasticities and the Inverse Hyperbolic Sine Transformation." *Oxford Bulletin of Economics and Statistics*, 82(1): 50–61.

Benmelech, Efraim, and Michal Zator. 2022. "Robots and Firm Investment." National Bureau of Economic Research Working Paper 29676.

Bloom, Nicholas, Raffaella Sadun, and John Van Reenen. 2016. "Management as a Technology?" National Bureau of Economic Research, Inc NBER Working Papers 22327.

Borusyak, Kirill, Xavier Jaravel, and Jann Spiess. 2021. "Revisiting Event Study Designs: Robust and Efficient Estimation."

Carbonero, Francesco, Ekkehard Ernst, and Enzo Weber. 2020. "Robots Worldwide: The Impact of Automation on Employment and Trade." IAB Working Papers.

Carree, Martin, Enrico Santarelli, and Ingrid Verheul. 2008. "Firm entry and exit in Italian provinces and the relationship with unemployment." *International Entrepreneurship and Management Journal*, 4: 171–186.

Cheng, Hong, Ruixue Jia, Dandan Li, and Hongbin Li. 2019. "The Rise of Robots in China." *Journal of Economics Perspectives*, 33(2): 71–88.

Chiacchio, Francesco, Georgios Petropoulos, and David Pichler. 2018. "The impact of industrial robots on EU employment and wages - A local labour market approach." Bruegel Working Papers 25186.

Clementi, Gian Luca, and Berardino Palazzo. 2016. "Entry, exit, firm dynamics, and aggregate fluctuations." *American Economic Journal: Macroeconomics*, 8(3): 1–41.

Cogley, Timothy, and James M Nason. 1995. "Output Dynamics in Real-Business-Cycle Models." *American Economic Review*, 85(3): 492–511.

Dargatz, D.A., and G.W. Hill. 1996. "Analysis of survey data." *Preventive Veterinary Medicine*, 28: 225–237.

Dauth, Wolfgang, Sebastian Findeisen, Jens Suedekum, and Nicole Woessner. 2021. "The Adjustment of Labor Markets to Robots." *Journal of the European Economic Association*, 19(6): 3104–3153.

Dechezleprêtre, Antoine, David Hémous, Morten Olsen, and Carlo Zanella. 2020. "Automating Labor: Evidence from Firm-Level Patent Data." Centre for Economic Performance, LSE CEP Discussion Papers dp1679.pdf.

De Ridder, Maarten. 2019. "Market Power and Innovation in the Intangible Economy." Centre for Macroeconomics (CFM) Discussion Papers 1907.

Dinlersoz, Emin, and Zoltan Wolf. 2018. "Automation, Labor Share, and Productivity: Plant-Level Evidence from U.S. Manufacturing." *Working Papers 18-39, Center for Economic Studies, U.S. Census Bureau*.

Dixon, Jay, Bryan Hong, and Lynn Wu. 2020. "The Robot Revolution: Managerial and Employment Consequences for Firms." NYU Stern School of Business Working Papers.

Fujii, Hidemichi, and Shunsuke Managi. 2018. "Trends and priority shifts in artificial intelligence technology invention: A global patent analysis." *Economic Analysis and Policy*, 58(C): 60–69.

Graetz, Georg, and Guy Michaels. 2018. "Robots at Work." *The Review of Economics and Statistics*, 100(5): 753–768.

Griliches, Zvi. 1969. "Capital-Skill Complementarity." *The Review of Economics and Statistics*, 51(4): 465–68.

Hamermesh, Daniel S. 1989. "Labor Demand and the Structure of Adjustment Costs." *The American Economic Review*, 79(4): 674–689.

Hopenhayn, Hugo. 1992. "Entry, Exit, and Firm Dynamics in Long Run Equilibrium." *Econometrica*, 60(5): 1127–1150.

Hubmer, Joachim, and Pascual Restrepo. 2021. "Not a Typical Firm: The Joint Dynamics of Firms, Labor Shares, and Capital–Labor Substitution." NBER Working Papers w28579.

Humlum, Anders. 2019. "Robot Adoption and Labor Market Dynamics." National Bureau of Economic Research Working Paper.

Imai, Kosuke, and In Song Kim. 2019. "When Should We Use Unit Fixed Effects Regression Models for Causal Inference with Longitudinal Data?" *American Journal of Political Science*, 63(2): 467–490.

International Federation of Robotics. 2014. "Robotics Data." data retrieved from International Federation of Robotics, `https://my.worldrobotics.org/`.

Jager, Angela, Cornelius Moll, Christoph Zanker, and Oliver Som. 2015. "Analysis of the impact of robotic systems on employment in the European Union." Fraunhofer ISI Working Papers.

Jaimovich, Nir, and Henry Siu. 2012. "Job Polarization and Jobless Recoveries." National Bureau of Economic Research, Inc NBER Working Papers 18334.

Kariel, Joel. 2021. "Job Creators or Job Killers? Heterogeneous Effects of Industrial Robots on UK Employment." *LABOUR*, 35(1): 52–78.

Koch, Michael, Ilya Manuylov, and Marcel Smolka. 2019. "Robots and Firms." *CESifo Working Paper*, 7608.

Kromann, Lene, and Anders Sorensen. 2019. "Automation, Performance, and International Competition: A Firm-Level Comparison of Process Innovation." *Working Papers 03-2015, Copenhagen Business School, Department of Economics.*

Kwon, Myung Joong, and Paul Stoneman. 1995. "The Impact Of Technology Adoption On Firm Productivity." *Economics of Innovation and New Technology*, 3(3-4): 219–234.

Kydland, Finn E., and Edward C. Prescott. 1991. "Hours and Employment Variation in Business Cycle Theory." *Economic Theory*, 1(1): 63–81.

Lashkari, Danial, Arthur Bauer, and Jocelyn Boussard. 2019. "Information Technology and Returns to Scale." Society for Economic Dynamics 2019 Meeting Papers 1380.

Manaresi, Francesco. 2015. "Net employment growth by firm size and age in Italy." Bank of Italy, Economic Research and International Relations Area Questioni di Economia e Finanza (Occasional Papers) 298.

Martin, Ralf. 2002. "Building the capital stock." The Centre for Research into Business Activity CeRiBA Working Paper.

Melitz, Marc J. 2003. "The impact of trade on intra-industry reallocations and aggregate industry productivity." *Econometrica*, 71(6): 1695–1725.

Olley, G. Steven, and Ariel Pakes. 1996. "The dynamics of productivity in the telecommunications equipment industry." *Econometrica*, 64(6): 1263–1297.

Seamans, Robert, and Manav Raj. 2018. "AI, Labor, Productivity and the Need for Firm-Level Data." *NBER Working Paper Series*.

Sedláček, Petr, and Vincent Sterk. 2017. "The Growth Potential of Startups over the Business Cycle." *American Economic Review*, 107(10): 3182–3210.

Sterk, Vincent, Petr Sedláček, and Benjamin Pugsley. 2021. "The Nature of Firm Growth." *American Economic Review*, 111(2): 547–79.

Susskind, R., and D. Susskind. 2015. *The Future of the Professions: How Technology Will Transform the Work of Human Experts.* Oxford University Press.

Vannutelli, Silvia, Sergio Scicchitano, and Marco Biagetti. 2021. "Routine biased technological change and wage inequality: do workers' perceptions matter?" Global Labor Organization (GLO) GLO Discussion Paper Series 763.

Zeira, Joseph. 1998. "Workers, Machines, and Economic Growth." *The Quarterly Journal of Economics*, 113(4): 1091–1117.

Zolas, Nikolas, Zachary Kroff, Erik Brynjolfsson, Kristina McElheran, David N Beede, Cathy Buffington, Nathan Goldschlag, Lucia Foster, and Emin Dinlersoz. 2020. "Advanced Technologies Adoption and Use by U.S. Firms: Evidence from the Annual Business Survey." National Bureau of Economic Research Working Paper 28290.

Survey Details

This section includes further details on the Bank of Italy's "Survey of Industrial and Service Firms".[15]

A1. Survey Design

The survey collects annual data on firm employment, investment, turnover, debt, and other structural information. It also has further detail on specific issues, which may not be asked annually, such as strategies, governance, technological and organisational factors. Up until 1998, only manufacturing firms with more than 50 employees were covered, but this was expanded in 1999 to include extractive and energy firms. Firms with more than 20 workers were included from 2002.

The survey population is divided into strata and firms are chosen randomly from each for the sample (one-stage stratified sample). Each strata are defined by economic activity, firm size, and region of head office. Employment is measured as the average number of workers during the year. Firms included in the previous year of the survey are always contacted, but may not be kept in the sample if they change activity class or fall below the threshold number of employees (they are replaced by firms of the same industry and size).

The data undergoes extensive quality checks: answers must fit within the range for the question; the panel data must be consistent; outliers must be checked. Statistical methods such as 'selective editing' are used to summarise the impact of outliers, to reduce the requirement to re-contact firms.

A2. Advanced Technologies Questions

The automation technology questions are contained here in full. In 2015, firms were asked if they use or intend to adopt the following advanced technologies:

1) Mobile broadband and the cloud (e.g. wireless technology, apps, smartphones, tablets, high-speed broadband, and cloud management software)

2) Artificial intelligence and big data (e.g. collection and use of large data sets that, with the application of specific algorithms for machine learning, can provide support to decision making; possible applications are: in remote access diagnostics, defining algorithms for financial investments, patent-related or legal searches)

3) The internet of things (e.g. the use of technologies that, by means of advanced sensors, allow apparatus to be used in the production and commercial processes promoting their integration)

4) Industrial robotics using artificial intelligence (advanced robotics)

[15] https://www.bancaditalia.it/pubblicazioni/metodi-e-fonti-note/metodi-note-2017/en_survey_methodology_invind.pdf?language_id=1

5) 3D printing

In 2017, firms were asked if they use or intend to adopt the following advanced technologies:

1) Cloud computing
2) E-commerce
3) Big data (e.g. the collection and use of large quantities of data which, also through machine learning algorithms, can assist decision-making; possible applications: distance diagnosis, financial trading algorithms, patent and legal research)
4) Internet of things (e.g. the use of technologies that, by means of advanced sensors,enable communication between the various devices used in production and business processes, facilitating their integration)
5) Artificial intelligence
6) Industrial robotics using artificial intelligence (advanced robotics)
7) 3D printing

In 2019, firms were asked if they use or intend to adopt the following advanced technologies:

1) Cloud computing
2) Big data
3) Artificial intelligence
4) Advanced robotics
5) 3D printing

A3. Firm Exit

There is some attrition in the panel, as firms leave and are replaced. "The firms observed in the previous edition of the survey are always contacted again if they are still part of the target population, while those no longer wishing to take part are replaced with others in the same branch of activity and size class."[16] The main reasons given for leaving the survey are change of activity and staff cutbacks to below the entry threshold. These numbers are somewhat higher than estimates of the Italian exit rate of 4 -8 % (Carree, Santarelli and Verheul, 2008).

[16] `https://www.bancaditalia.it/pubblicazioni/metodi-e-fonti-note/metodi-note-2017/en\_survey\_methodology\_invind.pdf?language_id=1`

Table A1—: Italian Survey Data: Firm Exit Proportions

Year	**% in subsequent year**	**% in preceding year**
2012	0.82	-
2013	0.84	0.82
2014	0.86	0.83
2015	0.84	0.84
2016	0.86	0.87
2017	0.85	0.83
2018	-	0.88

Note: the second column contains the proportion of firms appearing in that year which are present in the panel the following year. The third contains the proportion of firms appearing in that year which were present in the panel the previous year.

FURTHER FIGURES

Figure B1. : Cloud Computing Adoption by Firm Size

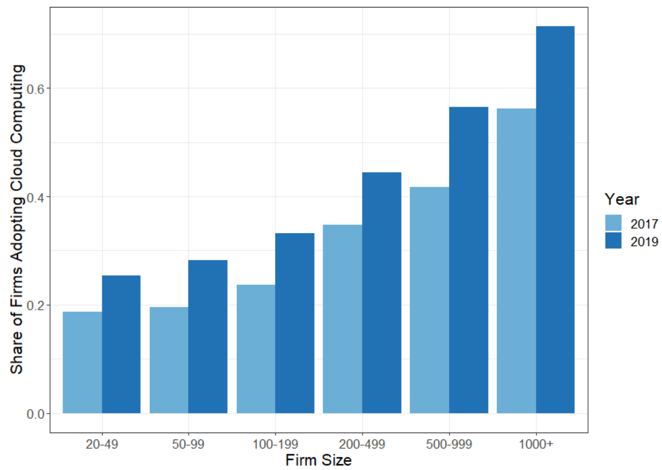


Figure B2. : Cloud Computing Adoption by Industry (2017)

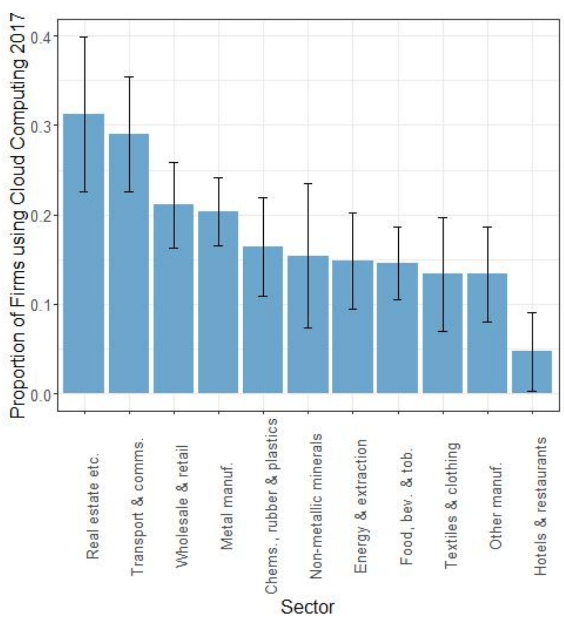


Figure B3. : AI & Big Data Adoption by Firm Size

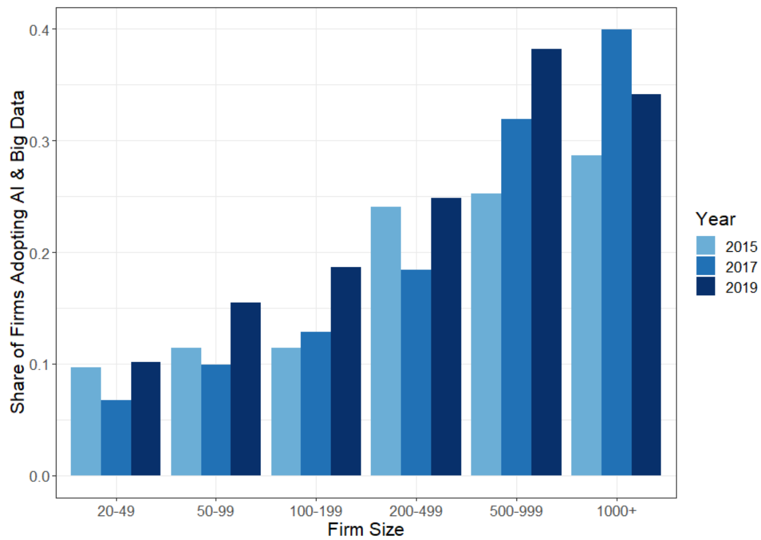


Figure B4. : Industry Adoption of AI & Big Data (2015)

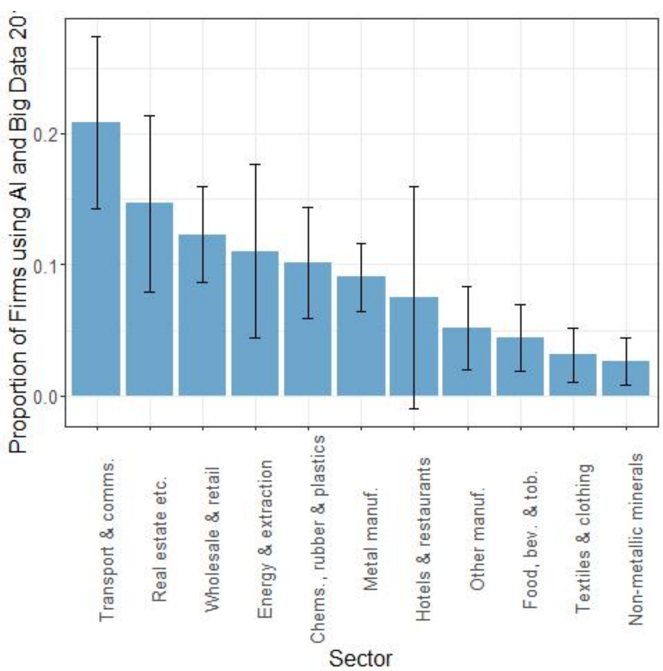
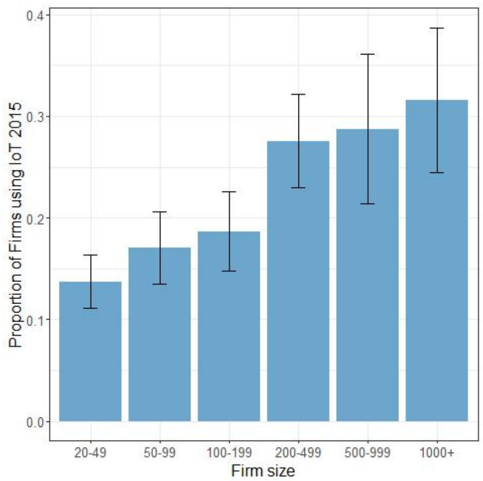


Figure B5. : Internet of Things Adoption across Age and Size Distributions (2015)



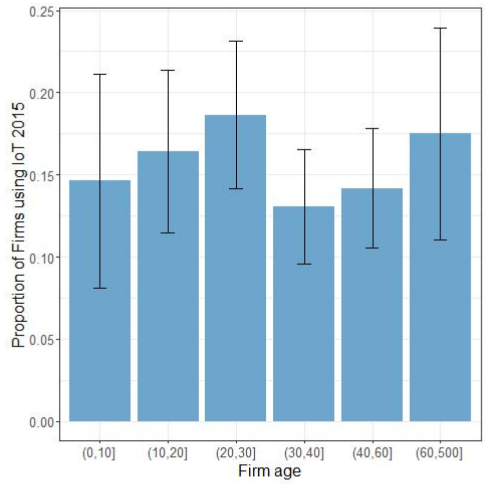
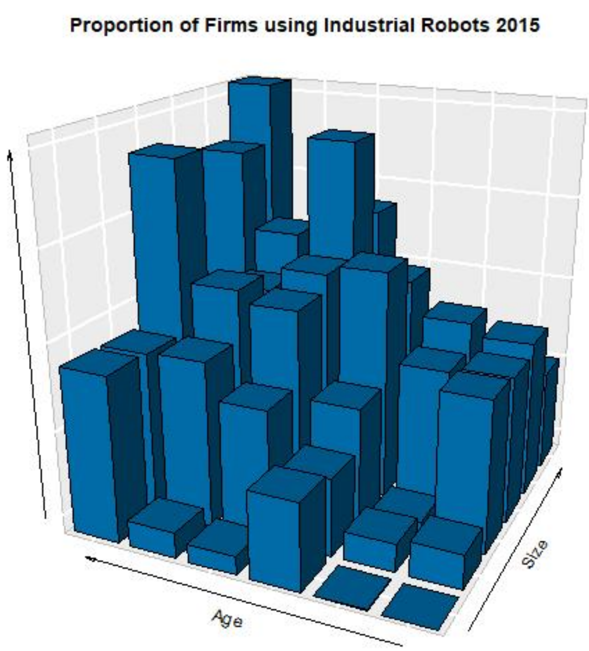


Figure B6. : Age-size Distribution of Firms using Robotics



Note: each bar is ratio of firms using Industrial Robots in each age $\times$ size cell.

Figure B7. : Adoption of Industrial Robotics by Industry (2017)

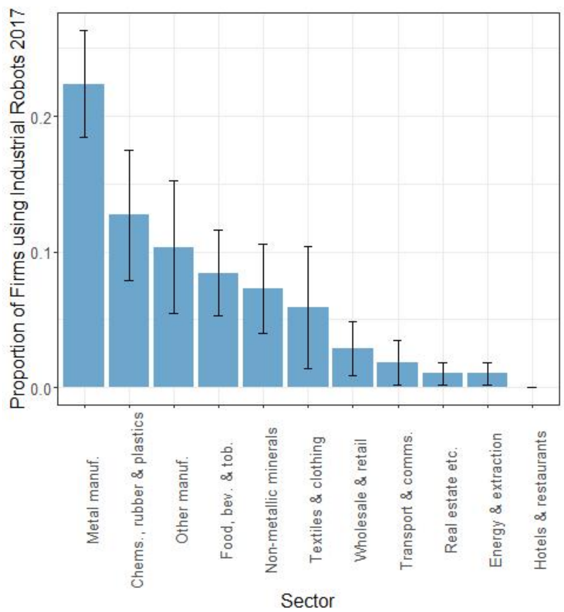


Figure B8. : 3D Printing Adoption by Firm Age and Size

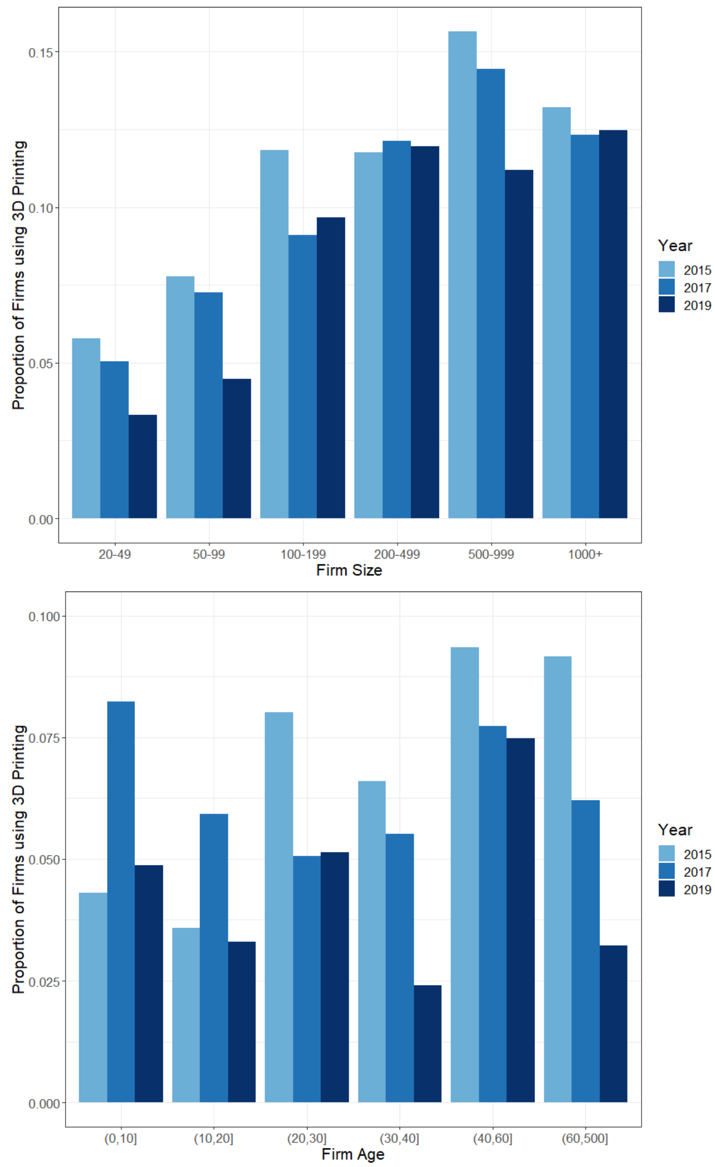


Figure B9. : Adoption of 3D Printing across Industries

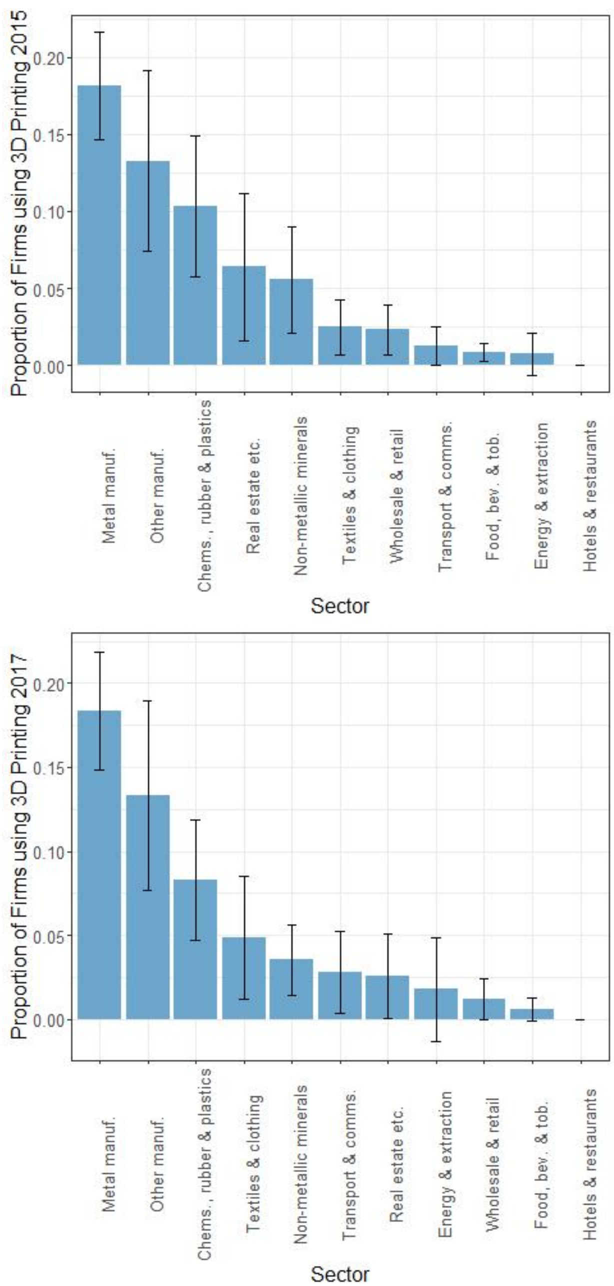


Figure B10. : Adoption of Automation Technologies by Firm Size and Age (2015)

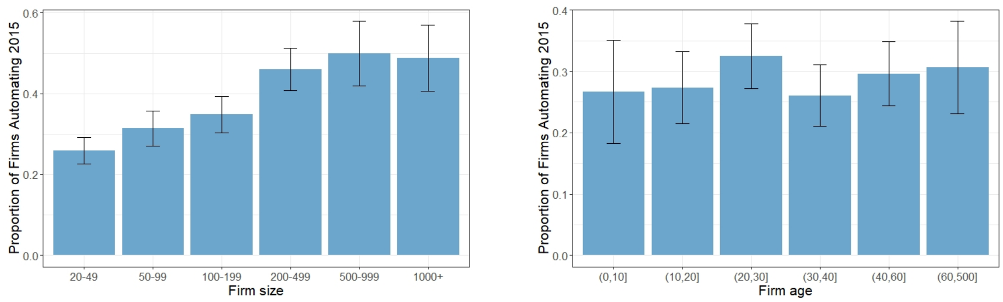


Figure B11. : Adoption of Automation Technologies by Firm Size and Age (2017)

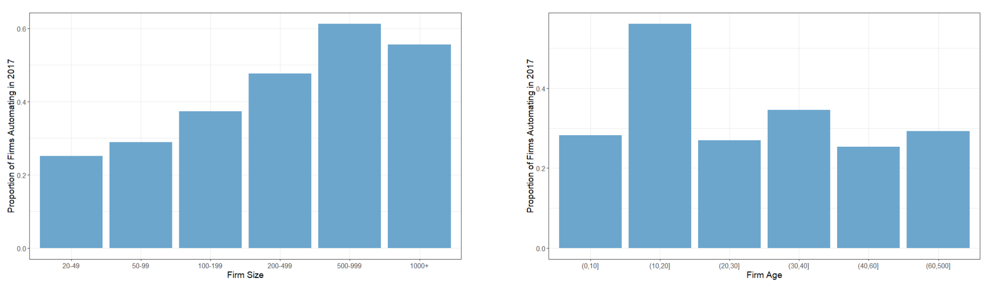


Figure B12. : Adoption of Automation Technologies by Firm Size and Age (2019)

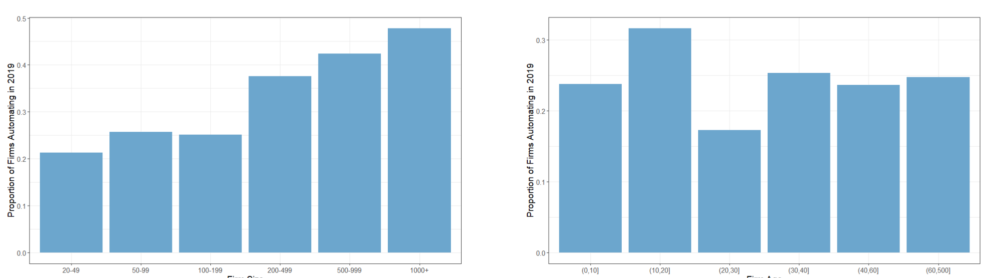
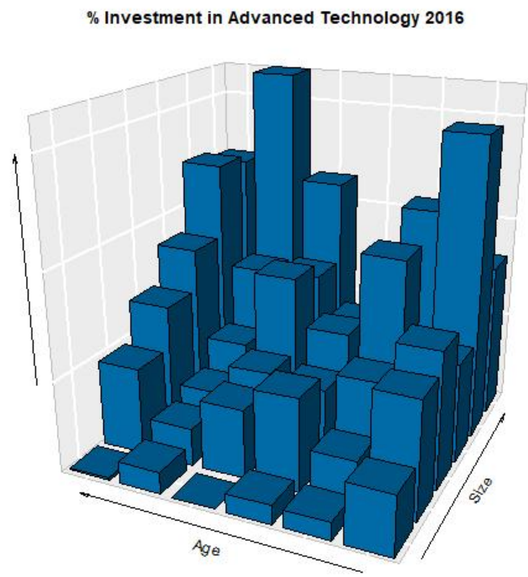


Figure B13. : Firm Age × Size Distributions of Advanced Technology Spending 2016/17



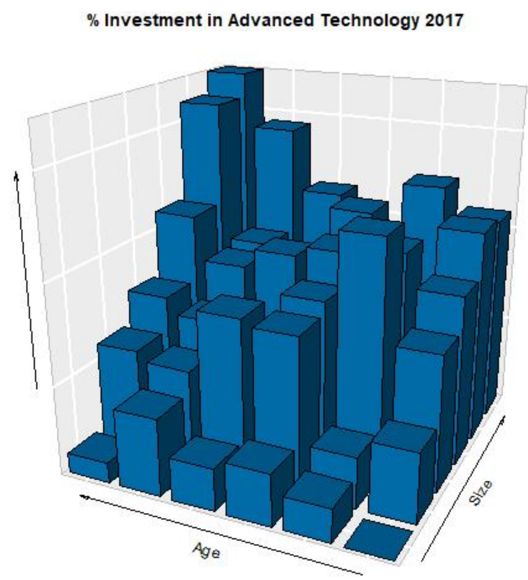


Figure B14. : Firm Age × Size Distributions of Advanced Technology Spending 2018/19

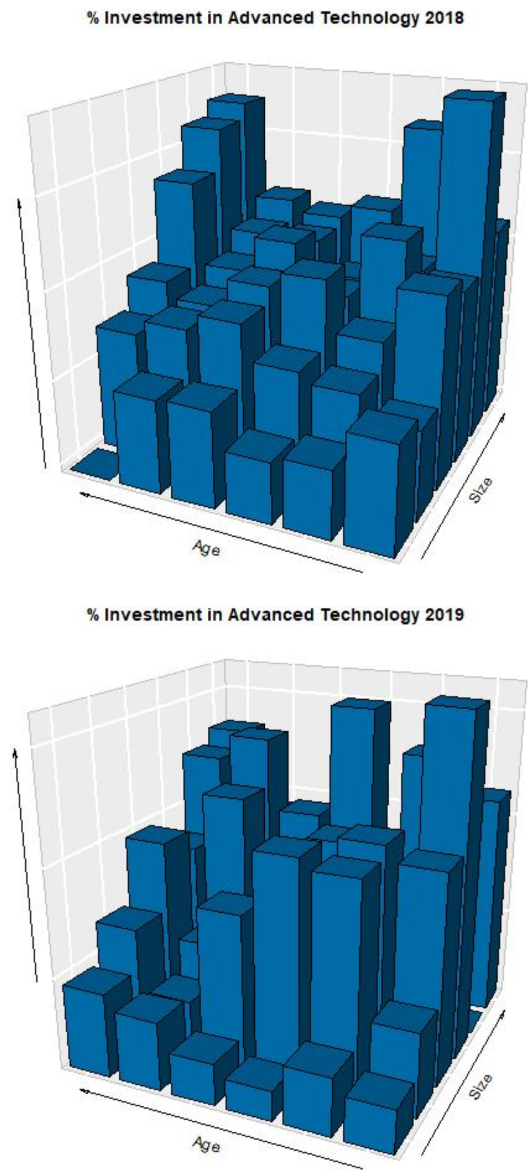


Figure B15. : Sectoral Distribution of Advanced Technology Spending 2016 - 2017

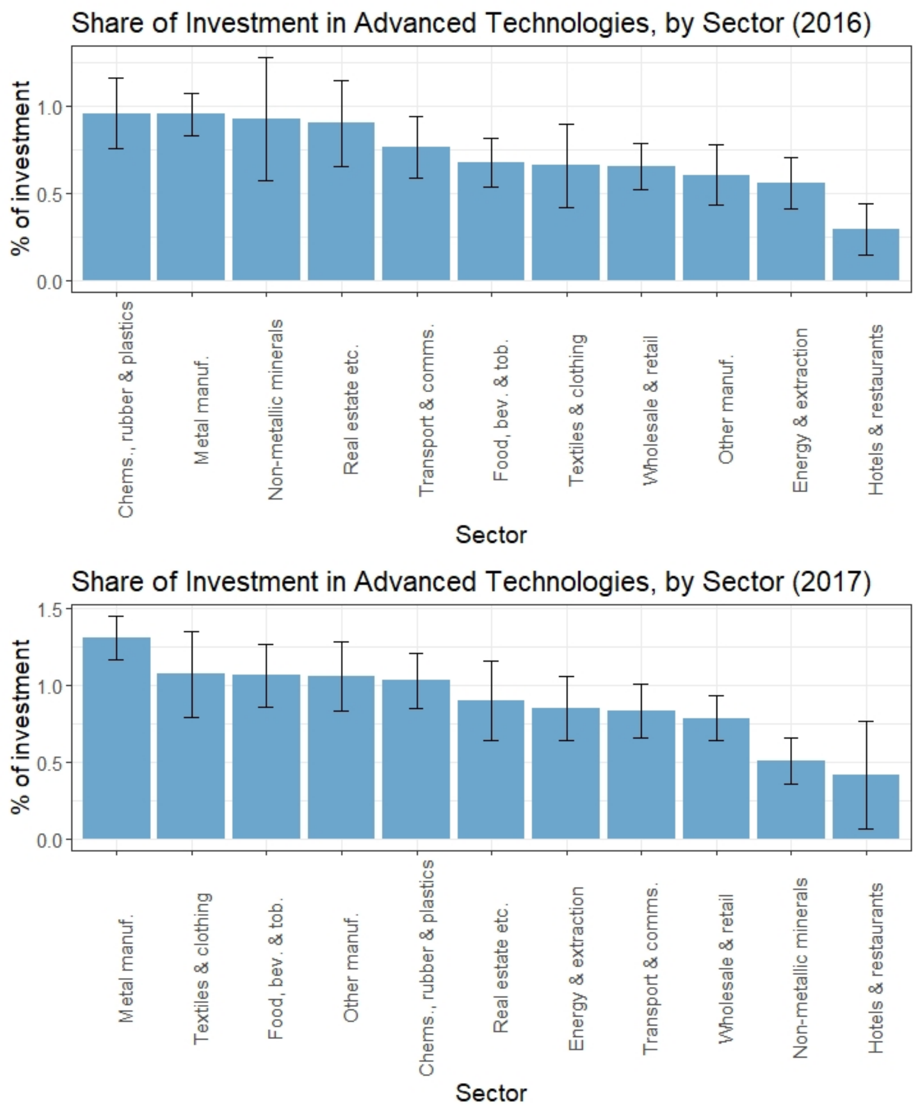


Figure B16. : Sectoral Distribution of Advanced Technology Spending 2018 - 2019

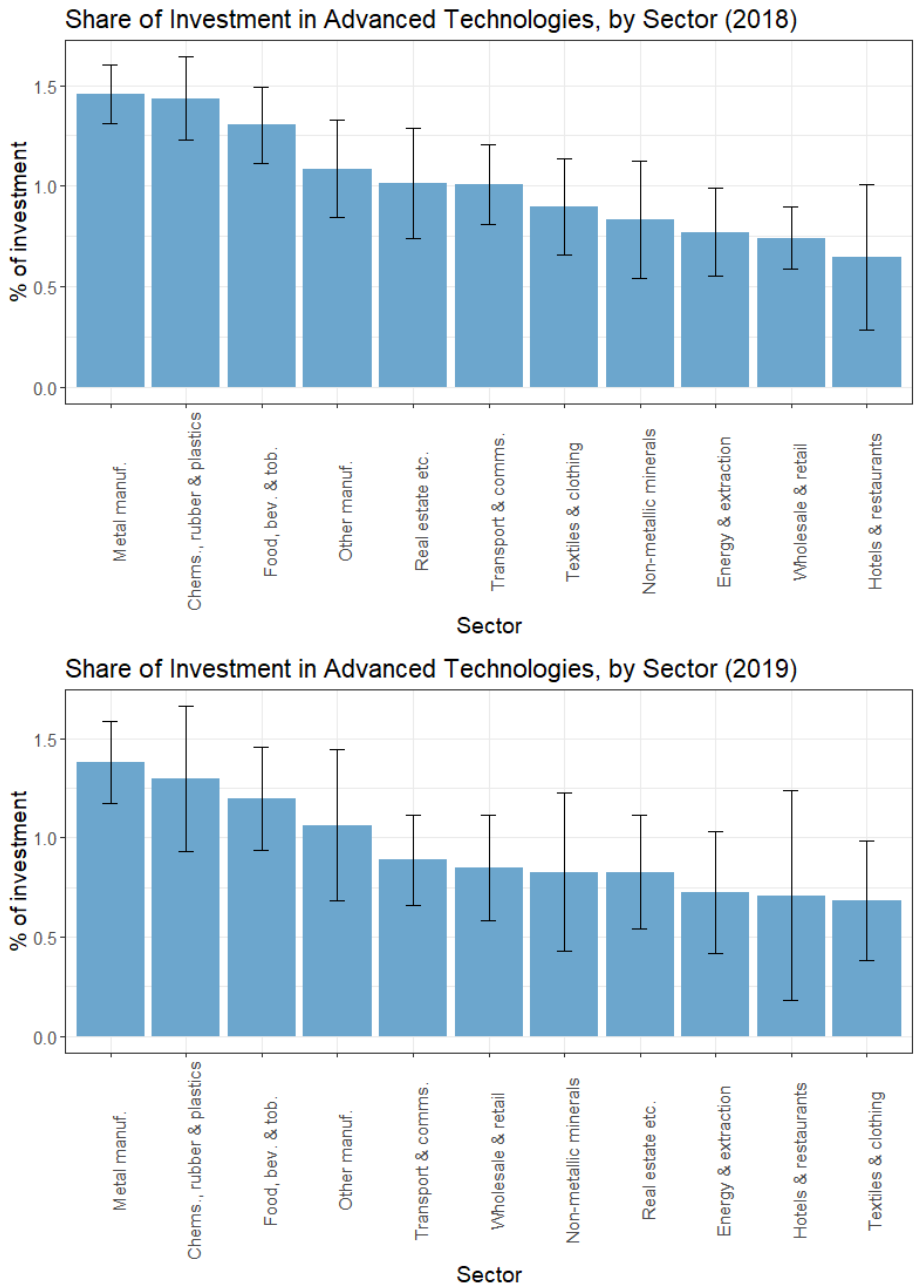
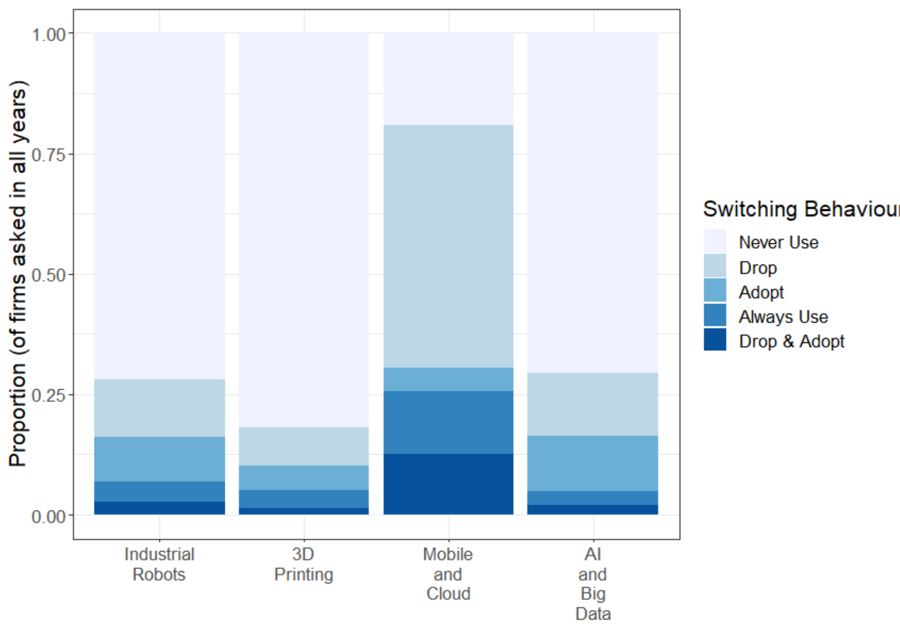


Figure B17. : Technology Switching Behaviour, 2015 - 2019



Note: Consider firms surveyed in 2015, 2017, and 2019. Never Use: firm does not adopt technology in any period. Drop: firm initially uses technology in 2015, but doesn't in subsequent periods. Adopt: firm doesn't initially use technology in 2015, but does adopt in a subsequent period. Always Use: firm uses technology in all periods. Drop & Adopt: firm initially uses technology in 2015, doesn't in a subsequent period, but then adopts it again in the future.

Figure B18. : Investment Share on Advanced Technology by Firm Age.

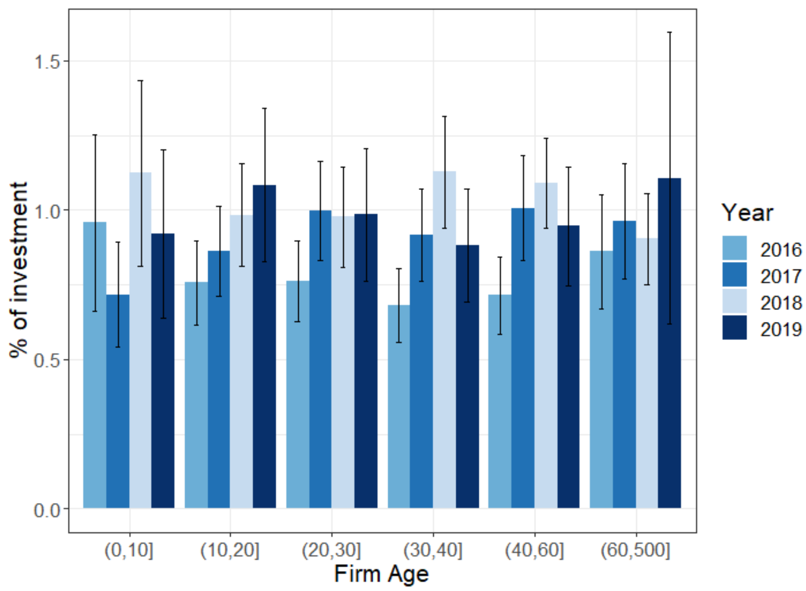
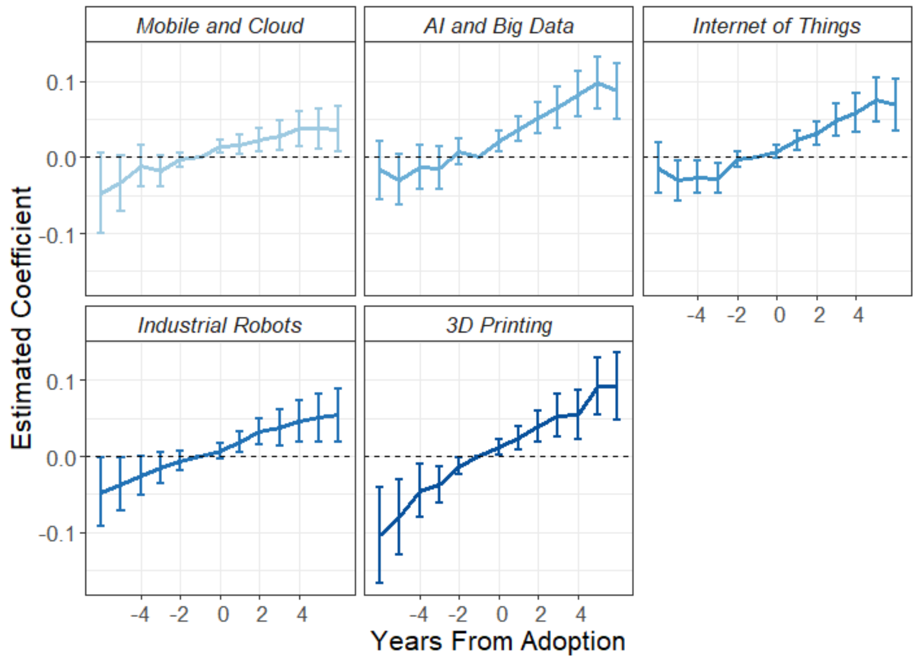


Figure B19. : Estimates from Event Study Regression

(a) Standard event study design on employment, without controlling for pre-trends *(regression run on 3,197 - 3,271 firms and 24,036 - 24,571 firm-year observations.)*



(b) Standard event study design on hours worked, without controlling for pre-trends *(regression run on 3,197 - 3,271 firms and 24,036 - 24,571 firm-year observations.)*

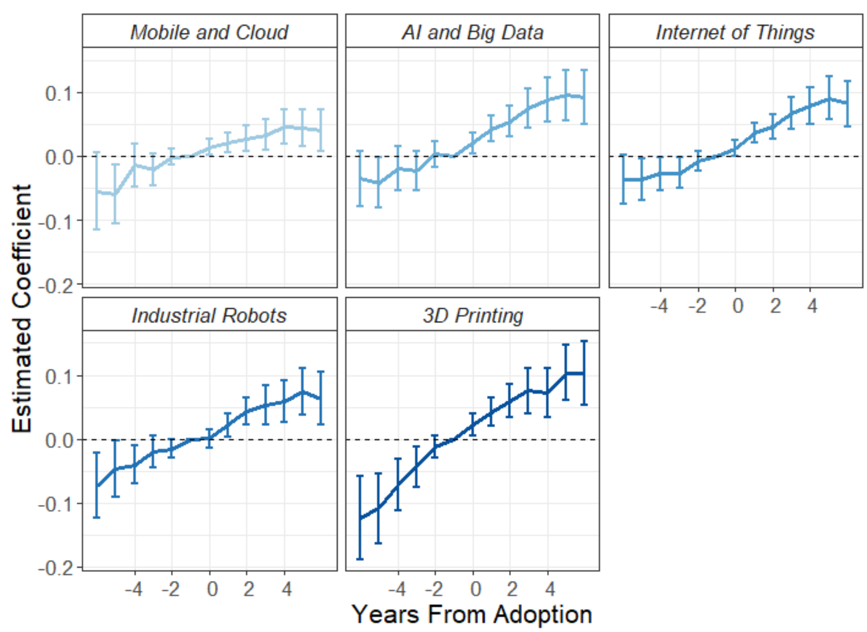
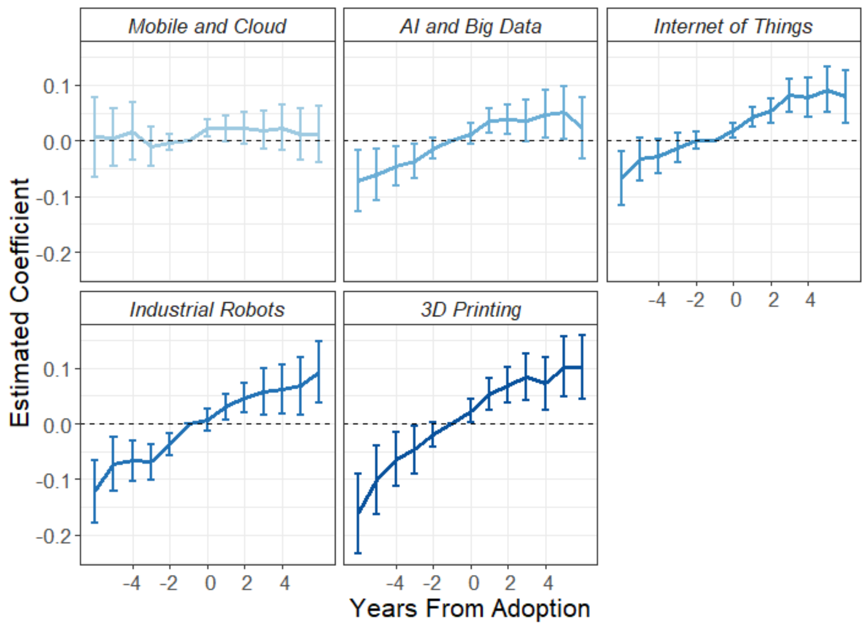


Figure B20. : Estimates from Event Study Regression

(a) Standard event study design on turnover, without controlling for pre-trends *(regression run on 3,197 - 3,271 firms and 24,036 - 24,571 firm-year observations.)*



(b) Standard event study design on wages, without controlling for pre-trends *(regression run on 3,197 - 3,271 firms and 24,036 - 24,571 firm-year observations.)*

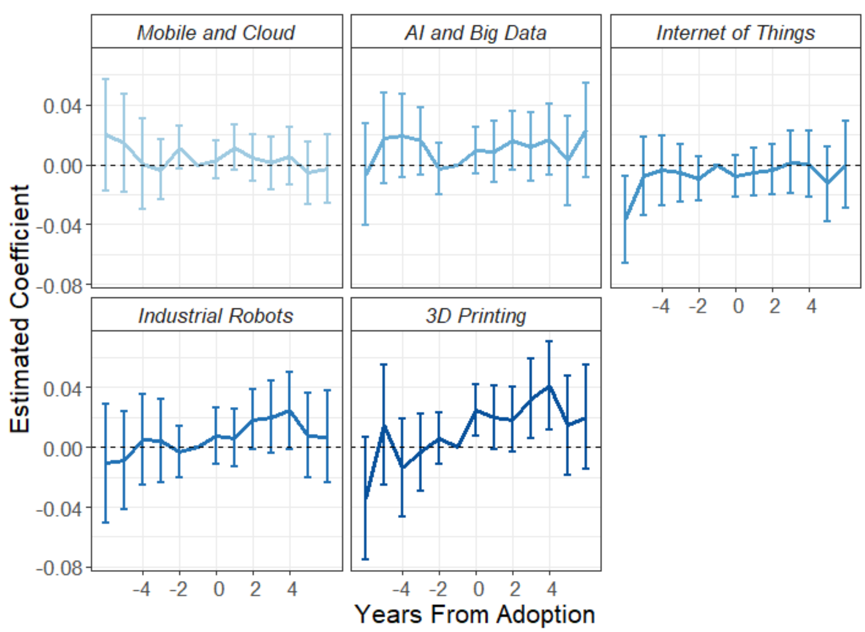
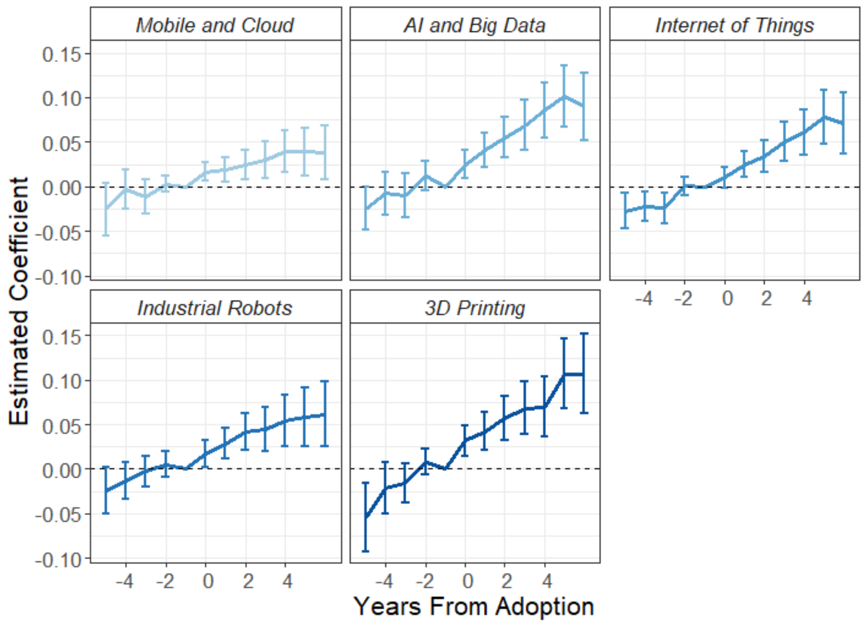


Figure B21. : Estimates from Event Study Regression

(a) Event study design on employment with pre-trends linearized *(regression run on 3,197 - 3,271 firms and 24,036 - 24,571 firm-year observations.)*



(b) Event study design on hours worked with pre-trends linearized *(regression run on 3,197 - 3,271 firms and 24,036 - 24,571 firm-year observations.)*

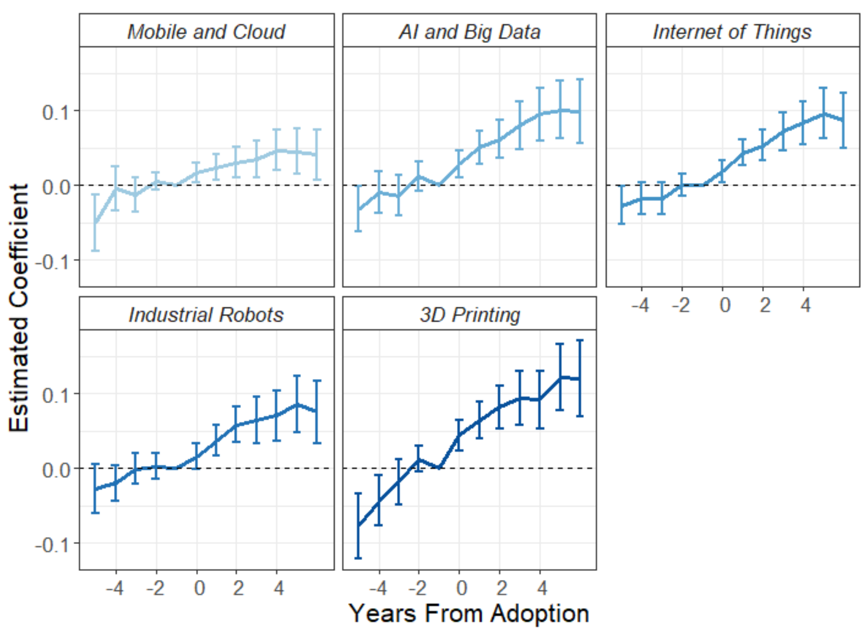
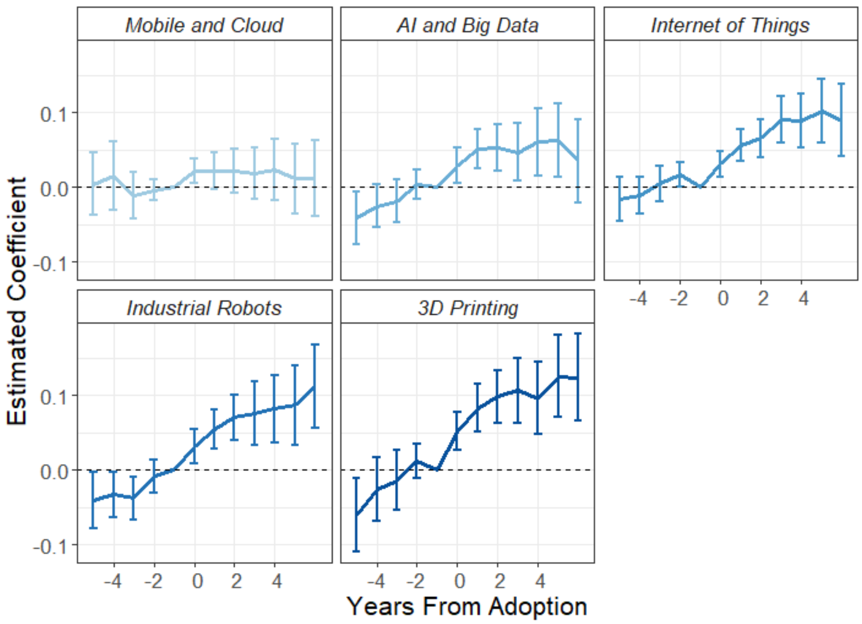


Figure B22. : Estimates from Event Study Regression

(a) Event study design on turnover with pre-trends linearized *(regression run on 3,197 - 3,271 firms and 24,036 - 24,571 firm-year observations.)*



(b) Event study design on wages with with pre-trends linearized *(regression run on 3,197 - 3,271 firms and 24,036 - 24,571 firm-year observations.)*

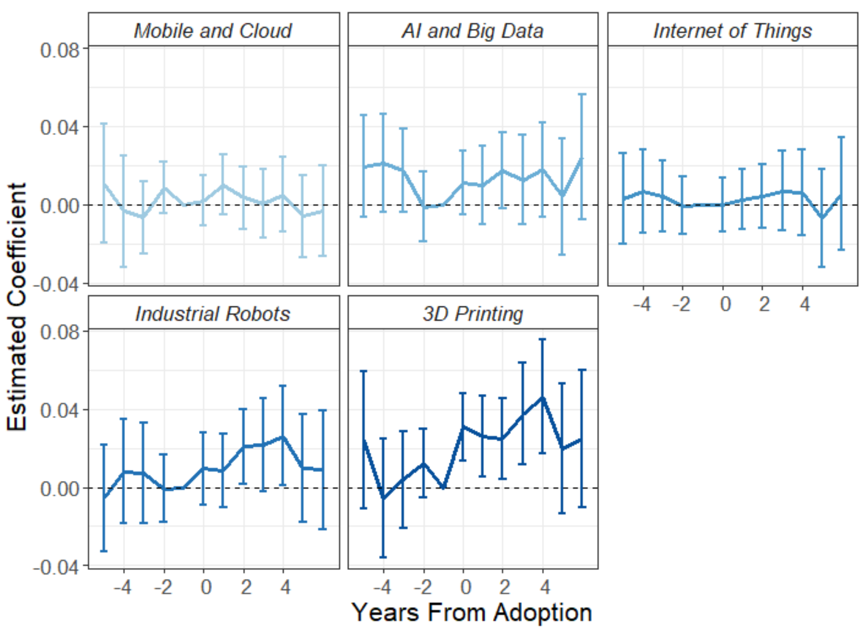


Figure B23. : Average Growth Rates (2010 - 2018) for Automation Adopters compared to Non-Adopters, Across Age Distribution

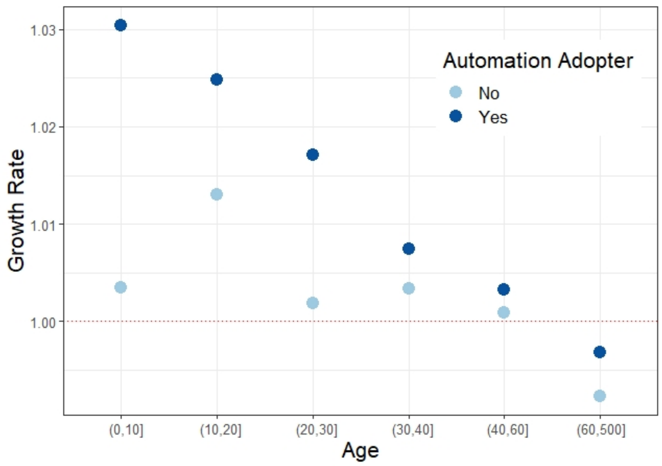


Figure B24. : Average Growth Rates (2010 - 2018) for Automation Adopters compared to Non-Adopters, Across Size Distribution

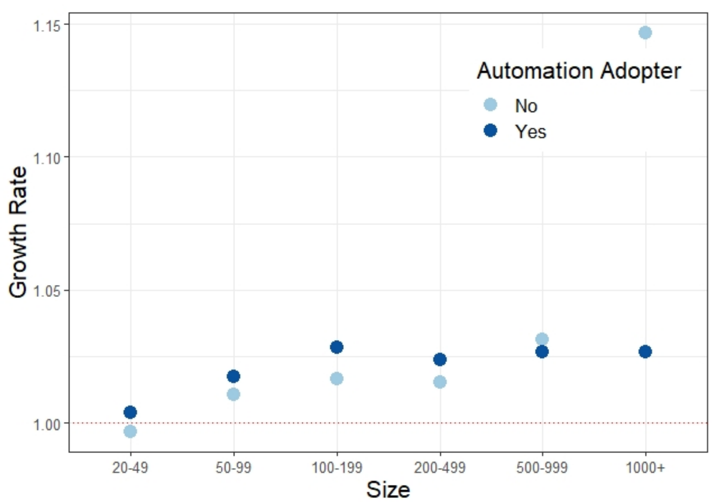


Figure B25. : Average Growth Rates (2010 - 2018) for Automation Adopters compared to Non-Adopters

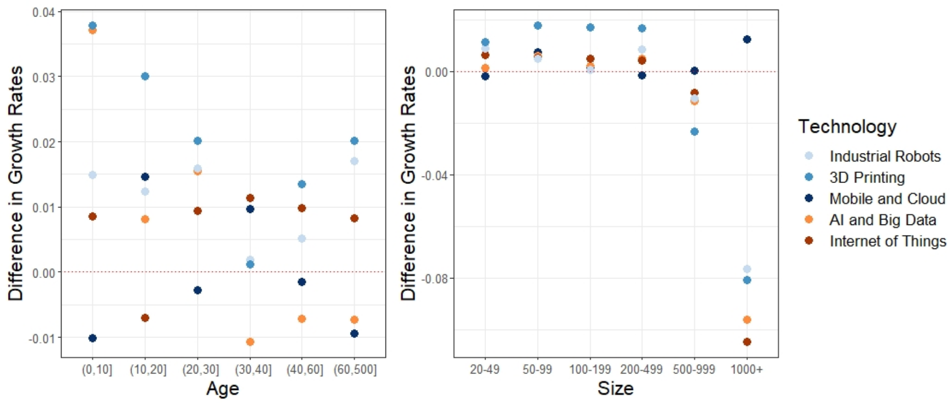
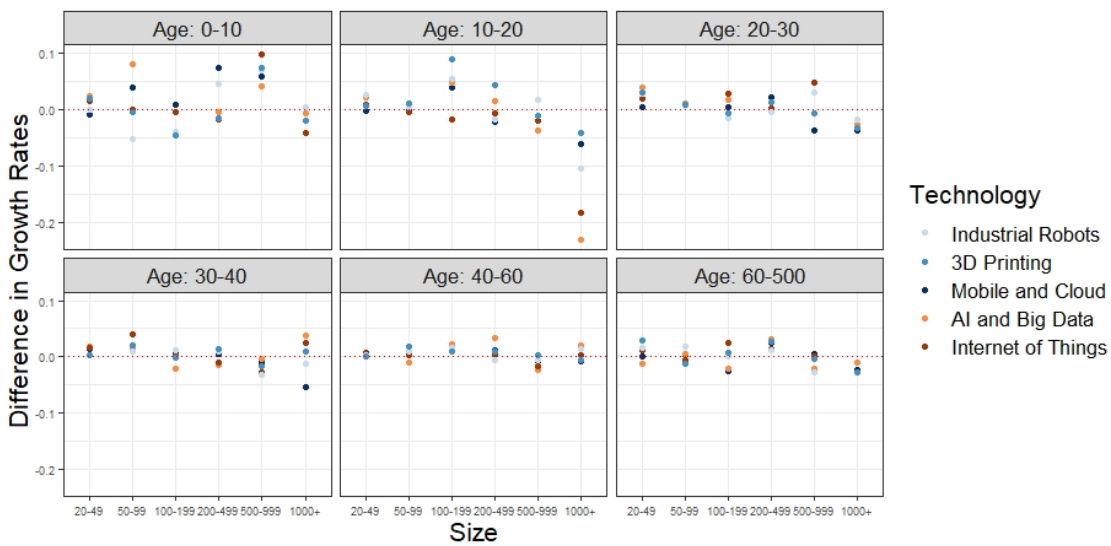


Figure B26. : Average Growth Rates (2010 - 2018) for Automation Adopters vs Non-Adopters, By Size and Age



FURTHER TABLES

Table C1—: Estimated Coefficients from Technology Adoption Regressions 2015

	Dependent variable: *Technology Adoption*									
	Mobile & Cloud		*AI & Big Data*		*Internet of Things*		*Industrial Robotics*		*3D Printing*	
log(Emp.)	0.033**	0.034**	0.039***	0.041***	0.052***	0.052***	0.040***	0.038***	0.027***	0.025***
	(0.010)	(0.011)	(0.009)	(0.009)	(0.009)	(0.009)	(0.006)	(0.006)	(0.006)	(0.006)
Age		−0.0005		−0.0007		−0.0002		0.0009**		0.0004
		(0.0005)		(0.0004)		(0.0004)		(0.0003)		(0.0003)

*Note: Estimates are significant at levels of 0.1%: ***, 1%: **, 5% *.*

Table C2—: Estimated Coefficients from Technology Adoption Regressions 2017

	Dependent variable: *Technology Adoption*									
	Cloud Computing		*AI & Big Data*		*Internet of Things*		*Industrial Robotics*		*3D Printing*	
log(Emp.)	0.074**	0.073**	0.064***	0.065***	0.076***	0.076***	0.036***	0.036***	0.033***	0.033***
	(0.010)	(0.010)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.004)	(0.004)
Age		0.0005		−0.0005*		−0.00007		0.0004**		−0.00006
		(0.0005)		(0.0004)		(0.0004)		(0.0003)		(0.0003)

*Note: Estimates are significant at levels of 0.1%: ***, 1%: **, 5% *.*

Table C3—: Estimated Coefficients from Technology Adoption Regressions 2019

	Dependent variable: *Technology Adoption*							
	Cloud Computing		*AI & Big Data*		*Industrial Robotics*		*3D Printing*	
log(Emp.)	0.084***	0.086***	0.060***	0.062***	0.054***	0.053***	0.031***	0.031***
	(0.016)	(0.016)	(0.013)	(0.013)	(0.007)	(0.007)	(0.006)	(0.006)
Age		−0.0008		−0.0011		0.0007		0.00001
		(0.0008)		(0.0008)		(0.0005)		(0.0002)

*Note: Estimates are significant at levels of 0.1%: ***, 1%: **, 5% *.*

Table C4—: Adoption of Multiple Technologies (2015)

	Mobile & Cloud	**AI & Big Data**	**IoT**	**Robots**	**3D Printing**
Mobile & Cloud	1.00	0.39	0.44	0.37	0.35
AI & Big Data	-	1.00	0.83	0.81	0.82
IoT	-	-	1.00	0.80	0.79
Robots	-	-	-	1.00	0.84
3D Printing	-	-	-	-	1.00

Note: proportion of technology adopters adopting another technology in 2015.

Table C5—: Adoption of Multiple Technologies (2017)

	Cloud	**AI**	**Big Data**	**IoT**	**Robots**	**3D Printing**	**E-Comm.**
Cloud	1.00	0.79	0.81	0.78	0.76	0.77	0.76
AI	-	1.00	0.90	0.83	0.88	0.88	0.77
Big Data	-	-	1.00	0.84	0.84	0.85	0.77
IoT	-	-	-	1.00	0.81	0.81	0.72
Robots	-	-	-	-	1.00	0.86	0.72
3D Printing	-	-	-	-	-	1.00	0.75
E-Comm.	-	-	-	-	-	-	1.00

Note: proportion of technology adopters adopting another technology in 2017.

Table C6—: Number of Firms Adopting Technologies (2015)

	Mobile & Cloud	**AI & Big Data**	**IoT**	**Robots**	**3D Printing**
Yes	2,524	440	642	485	360
No	934	2,953	2,742	2,912	3,037
NA	937	1,002	1,011	998	998
% Yes (all)	*0.57*	*0.10*	*0.15*	*0.11*	*0.08*
% Yes (answered)	*0.73*	*0.13*	*0.19*	*0.14*	*0.11*

Note: Answers from firms on use of advanced technologies in 2015, along with proportion of firms adopting each technology (of all firms, and of firms that were asked).

Table C7—: Share of Firms Adopting Individual Technologies (2015)

	Mobile & Cloud	**AI & Big Data**	**IoT**	**Robots**	**3D Printing**
All firms	0.56	0.09	0.12	0.06	0.05
Answered firms	0.73	0.11	0.16	0.08	0.07

Note: The weighted proportions of firms that use advanced technologies in 2015.

Table C8—: Share of Firms Adopting Technologies (2015)

	Any Tech.	**Digital Tech.**	**Physical Tech.**
All firms	0.23	0.16	0.10
Answered firms	0.30	0.21	0.13

Note: The weighted proportions of firms that use combinations of advanced technologies in 2015.

Table C9—: Number of Firms Adopting Technologies (2017)

	Cloud	**AI**	**Big Data**	**IoT**	**Robots**	**3D Printing**	**E-Comm.**
Yes	849	226	416	733	477	375	871
No	2,976	3,591	3,404	3,092	3,349	3,443	2,974
NA	566	574	571	566	565	573	546
% Yes (all)	*0.19*	*0.05*	*0.10*	*0.17*	*0.11*	*0.09*	*0.20*
% Yes (answered)	*0.22*	*0.06*	*0.11*	*0.19*	*0.12*	*0.10*	*0.23*

Note: answers from firms on use of advanced technologies in 2017, along with proportion of firms adopting each technology (of all firms, and of firms that were asked).

Table C10—: Share of Firms Adopting Individual Technologies (2019)

	Cloud	**AI**	**Big Data**	**IoT**	**Robots**	**3D Printing**	**E-Comm.**
All firms	0.18	0.03	0.06	0.11	0.07	0.05	0.19
Answered firms	0.21	0.03	0.07	0.13	0.08	0.06	0.22

Note: weighted proportions of firms that use advanced technologies in 2017.

Table C11—: Share of Firms Adopting Technologies (2017)

	Any Tech.	**Digital Tech.**	**Physical Tech.**
All firms	0.28	0.25	0.10
Answered firms	0.33	0.29	0.11

Note: weighted proportions of firms that use combinations of advanced technologies in 2017.

Table C12—: Number of Firms Adopting Technologies (2019)

	Cloud	**AI**	**Big Data**	**Robots**	**3D Printing**
Yes	633	149	293	317	192
No	1,440	1,916	1,778	1,751	1,877
NA	1,116	1,124	1,118	1,121	1,120
% Yes (all)	*0.20*	*0.05*	*0.09*	*0.10*	*0.06*
% Yes (answered)	*0.31*	*0.07*	*0.14*	*0.15*	*0.09*

Note: answers from firms on use of advanced technologies in 2019, along with proportion of firms adopting each technology (of all firms, and of firms that were asked).

Table C13—: Share of Firms Adopting Individual Technologies (2019)

	Cloud	**AI**	**Big Data**	**Robots**	**3D Printing**
All firms	0.18	0.03	0.07	0.04	0.03
Answered firms	0.28	0.04	0.11	0.07	0.05

Note: weighted proportions of firms that use advanced technologies in 2019.

Table C14—: Share of Firms Adopting Technologies (2019)

	Any Tech.	**Digital Tech.**	**Physical Tech.**
All firms	0.24	0.20	0.06
Answered firms	0.37	0.32	0.10

Note: weighted proportions of firms that use combinations of advanced technologies in 2019.

Table C15—: Advanced Technology Adopters vs Non-Adopters: Summary Statistics 2015

	Mobile & Cloud		*AI & Big Data*	
	Adopters	**Non-Adopters**	**Adopters**	**Non-Adopters**
Age	34.9	**35.7**	33.0	**35.4**
Log(employment)	**3.94**	3.83	**4.14**	3.89
Log(wage per worker) (€)	**10.28**	10.28	**10.35**	10.27
Hours per worker (weekly)	**31.46**	31.40	**31.65**	31.49
Turnover per worker (thou., €)	**459**	345	**499**	423
Fixed investment per worker (thou., €)	**10.9**	8.12	**14.5**	9.61
% blue-collar	0.51	**0.61**	0.43	**0.55**
% export sales	0.09	0.11	0.06	**0.10**
Terminations per worker	**0.18**	0.14	0.17	0.17
Hirings per worker	**0.19**	0.13	0.18	0.17
Number of firms	2524	934	440	2953
	Internet of Things		*Industrial Robotics*	
	Adopters	**Non-Adopters**	**Adopters**	**Non-Adopters**
Age	35.1	35.1	**41.1**	34.7
Log(employment)	**4.13**	3.87	**4.22**	3.88
Log(wage per worker) (€)	**10.32**	10.27	**10.33**	10.28
Hours per worker (weekly)	**31.81**	31.46	31.05	**31.56**
Turnover per worker (thou., €)	397	**439**	331	**442**
Fixed investment per worker (thou., €)	**12.4**	9.78	8.22	**10.4**
% blue-collar	0.51	**0.55**	**0.64**	0.53
% export sales	0.04	**0.11**	0.05	**0.10**
Terminations per worker	0.16	0.17	0.11	**0.17**
Hirings per worker	0.18	0.18	0.11	**0.18**
Number of firms	642	2742	485	2912
	3D Printing			
	Adopters	**Non-Adopters**		
Age	**38.5**	34.9		
Log(employment)	**4.16**	3.89		
Log(wage per worker) (€)	**10.33**	10.28		
Hours per worker (weekly)	**31.65**	31.52		
Turnover per worker (thou., €)	273	**444**		
Fixed investment per worker (thou., €)	5.71	**10.5**		
% blue-collar	0.56	0.54		
% export sales	0.11	0.10		
Terminations per worker	0.08	**0.17**		
Hirings per worker	0.11	**0.18**		
Number of firms	360	3037		

Note: Summary statistics from 2015 for firms that do and don't use advanced technologies. All values (other than number of observations) are weighted means. Bold values are the larger of the two, if there is a significant difference between adopters and non-adopters at the 1% level, computed with Welch's t-test and the Welch-Sattherwaite equation for degrees of freedom.

Table C16—: Automating Firms vs Traditional Firms: Summary Statistics

	Employment	*log(Hours)*	*log(Wage)*	*Age*
'Digital' Automating Firms	59.6	7.41	10.32	34.1
Non-Adopters	47.6	7.40	10.27	35.4
'Physical' Automating Firms	63.8	7.40	10.31	38.7
Non-Adopters	48.1	7.40	10.28	34.6

Note: 'Digital' automation technologies are Mobile & Cloud, AI & Big Data, and the Internet of Things. 'Physical' automation technologies are Industrial Robotics, and 3D Printing. Note that hours are average hours per worker, over the year.

Table C17—: Binned Variables Firm Growth Regressions 2008 - 2019

Dependent variable: *Employment Growth*					
Size	*50-99*	*100-199*	*200-499*	*500-999*	*1000+*
	0.014^{***}	0.021^{***}	0.022^{***}	0.029^{***}	0.028^{***}
	(0.002)	(0.003)	(0.002)	(0.004)	(0.004)
Size (control for Age)	*50-99*	*100-199*	*200-499*	*500-999*	*1000+*
	0.014^{***}	0.022^{***}	0.023^{***}	0.030^{***}	0.029^{***}
	(0.002)	(0.003)	(0.002)	(0.004)	(0.004)
Age	*10-20*	*20-30*	*30-40*	*40-60*	*60+*
	-0.002	-0.006	-0.008	-0.011^{*}	-0.018^{**}
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Age (control for Size)	*10-20*	*20-30*	*30-40*	*40-60*	*60+*
	-0.002	-0.006	-0.007	-0.011^{*}	-0.021^{***}
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)

Note: Coefficients represent estimated growth rates relative to omitted bin (for firm size: 20 - 49 employees; for firm age: 0 - 10 years). Regression includes year fixed effects. $N = 38,702$. *Estimates are significant at levels of 1%: ***, 5%: **, 10% *.*

Table C18—: Estimated Coefficients from Advanced Tech. Investment Regressions

Dependent variable: *Share of Investment in Advanced Tech.*						
	2016 ($N = 3756$)			2017 ($N = 3926$)		
log(Emp.)	0.279***	0.278***	0.254***	0.337***	0.329***	0.299***
	(0.025)	(0.025)	(0.026)	(0.028)	(0.028)	(0.028)
Age		−0.0000004	0.0002		0.0034**	0.0026*
		(0.001)	(0.001)		(0.001)	(0.001)
	2018 ($N = 3715$)			2019 ($N = 2075$)		
log(Emp.)	0.294***	0.295***	0.261***	0.275***	0.274***	0.258***
	(0.030)	(0.030)	(0.030)	(0.039)	(0.039)	(0.040)
Age		−0.0004	−0.002		0.0005	−0.001
		(0.001)	(0.001)		(0.001)	(0.002)
Fixed Effects			✓			✓

*Note: Estimates are significant at levels of 0.1%: ***, 1%: **, 5% *. Fixed effects are sector and region.*

Table C19—: Estimated Coefficients from Firm Growth Regressions 2010 - 2018

Dependent variable: *Employment Growth*								
log(Emp.)	0.014***	0.015***	0.014***	0.015***	0.366***	0.366***	0.365***	0.364***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.09)	(0.09)	(0.09)	(0.09)
Age		−0.0003***		−0.0003***		0.0005		−0.0006
		(0.00007)		(0.00007)		(0.0004)		(0.0004)
Sector FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE			✓	✓			✓	✓
Firm FE					✓	✓	✓	✓
N	20450	20446	20450	20446	20450	20446	20450	20446

*Note: Estimates are significant at levels of 0.1%: ***, 1%: **, 5% *.*

Table C20—: Average Growth Rates by Technology, for Adopters and Non-Adopters

	Cloud Computing	*AI & Big Data*	*IoT*	*Industrial Robotics*	*3D Printing*
Adopters	1.0065	1.0133	1.0133	1.0122	1.0171
Non-Adopters	0.9989	1.0036	1.0033	1.0038	1.0037

Note: Firms are compiled in a panel from 2010 - 2018 and labelled as adopters or non-adopters of each technology. Each number here represents the average employment growth rate of firms in these groups over this time period.

PERPETUAL INVENTORY METHOD

Firm-level productivity estimation is computed using control function methods. These require firm-level capital stock. This section explains the Perpetual Inventory Method (PIM) used to construct a measure of capital stock, followed by the productivity estimation approaches.

PERPETUAL INVENTORY METHOD. — The Perpetual Inventory Method (PIM) allows construction of firm-level capital stocks when such data is unavailable, but investment data is present. The method here follows Martin (2002). The PIM is constructed using the following equation:

$$K_t = (1-\delta)K_{t-1} + i_t.$$

where K_t is the capital stock in period t, and i_t is investment in period t. However, to use this method, we need K_0 - the initial capital stock of a firm - which is not in this survey. To construct this series, each firm's K_0 is an employment-weighted share of total investment in the year they first appear in the survey. Capital stock is then constructed for all future years with the above equation. The depreciation rate is taken to be 10%.