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ORIGINAL ARTICLE

Technology and productivity growth

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Abstract

Establishment-level productivity within narrowly defined industries is widely dispersed. This productivity dispersion may arise because the process of adoption and diffusion of an innovation is complex, as new innovative establishments enter and other less innovative establishments shrink (and may even exit). Given that much innovation is embodied in new businesses, the increase in business formations since the start of the pandemic may be an optimistic sign for the future—but should be viewed against the backdrop of an overall decline in business dynamism. Artificial intelligence (AI) is arguably the most-touted productivity-enhancing technology on the horizon. Firms that have made the most use of AI—mainly larger ones—are growing faster than others through product innovation, but as yet their productivity performance is not noticeably better than their peers. This may change over time, as the adoption of AI technologies becomes more widespread, and the use of AI technologies is directed more toward productivity enhancement.

Keywords Productivity · Technology · Artificial Intelligence · Innovation

1 LUCIA FOSTER

Productivity is a large and complex topic. In trying to understand productivity growth, there are many underlying factors that we have to keep in mind, for example, things like demographics. In a panel earlier today, there was a discussion about the paucity of immigration in the United States—which is an example of something that could impact productivity growth. It would be easy to get overwhelmed by all of these factors and I only have a few minutes to talk to you.

What I decided to do today was to focus on a very narrow slice. I am going to be talking about productivity growth and reallocation and innovation. I picked this slice because I think there are some interesting new data products out of the Census Bureau that suggest it is a sort of "on the one hand/on the other hand" story about what may be happening with productivity growth.

To motivate the connection between productivity growth and reallocation, I will note that an important determinant of industry, and hence, aggregate, productivity growth is the movement of resources from less productive to more productive businesses (see for example, (Foster et al. 2001)). This reallocation takes place as new businesses enter, high-productivity businesses grow, while low-productivity businesses contract, and some may even exit.

Reallocation is an important mechanism because there are large, persistent differences in establishment productivity levels, even within narrowly defined industries (see Dispersion Statistics on Productivity (DiSP) (census.gov). One example is cement. If you looked at all the establishments in cement, and you had them in a productivity distribution, establishments at the 75th percentile in that productivity distribution are about two and a half times more productive than establishments at the 25th percentile. In some industries, this dispersion is even larger. For example, in computers, establishments at the 75th percentile are about six and half times more productive than establishments at the 25th percentile.

This difference in productivity, which we call "dispersion"—can reflect many things, such as technology adoption, managerial ability, and so on. But I am just going to

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focus on two things it might reflect: It could reflect frictions and distortions such as barriers to entry, or it could reflect the presence of innovative activity.

Frictions and distortions, such as barriers to entry, can slow or distort the reallocation process and lead to slower productivity growth. But when there is an innovation, the impact on productivity growth is complicated because of the experimental nature of innovation. In empirical work, we find evidence that innovation leads to productivity growth, but with a lag.

A general framework to help understand these dynamics is inspired by Gort and Klepper's (1982) work. Here is a rough sketch of the dynamics: within an industry, there is an innovation. It could be a process innovation or a product innovation. This pulls a lot of entrants into that industry, so there is a time period of entry. During this time period, the businesses that have entered and the businesses that are picking up this new innovation are experimenting with it. Some are doing a great job, so they are at the top of the productivity distribution. Others are not doing such a great job, they are at the lower end of the productivity distribution. And then there is this shakeout time period where the reallocation happens. Figure 1 provides a rough schematic of the dynamics.

Those businesses that are doing well continue and grow. Those businesses that are not doing well may shrink and may actually exit. Taking this to the micro-level data, we do not have a direct measure of innovation, so what we have done is break the data into two groups: high tech and non-high tech. Think computers (high tech) and cement (non-high tech).

We run a regression for productivity dispersion and for productivity growth: two separate regressions with entry and high-tech dummies over three three-year periods (see Foster et al. 2021). The first 3-year period is when the innovation entry happens. The second three-year period is experimentation. And then the third three-year period is shakeout (reallocation).

We use industry aggregates using micro-level data from the Census Bureau's Longitudinal Business Database, which has about six million businesses every year. And the results as depicted in Fig. 2 show, following a period

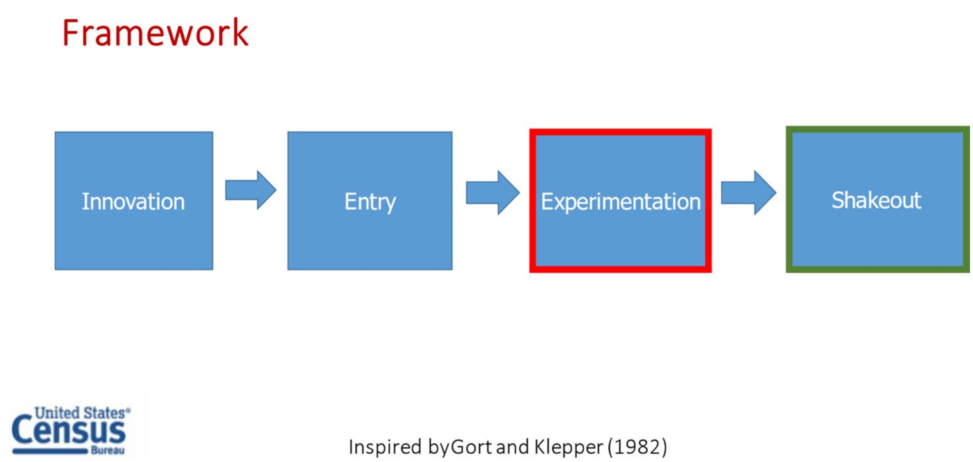


Fig. 1 Framework Inspired by Gort and Klepper (1982)

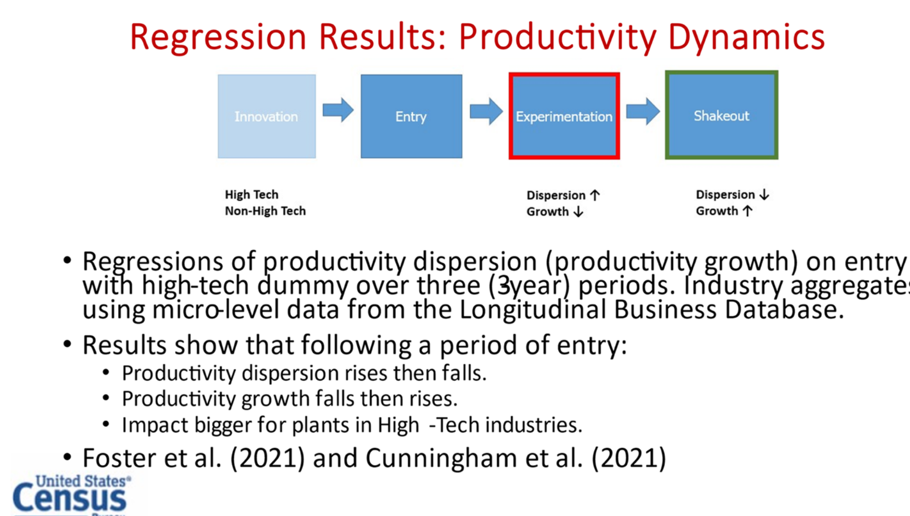


Fig. 2 Regression results

of entry, this productivity gap rises in the experimentation period. Productivity *dispersion* goes up.

At the same time, productivity *growth* may go down, because it may be that the businesses that are having the trouble with the experiment are actually overwhelming those businesses that are successful. Then, in the next three-year period, the shakeout (or reallocation) period, we actually see that productivity *dispersion* declines. The businesses that have been at the lower end of the productivity distribution have now shrunk or exited. The gap has declined, and productivity *growth* may actually increase at that point. The takeaway from here is that there is a lag in productivity growth with response to innovation. The impact that we see is higher for businesses in high-tech industries, which is where we would expect to see most of the innovation occurring.

With this framework in mind, I am now going to show you some of the "on the one hand, on the other hand" evidence from Census Bureau data products. Let me first talk a little bit about what we have seen recently in reallocation. Those of you who attended John Haltiwanger's talk earlier today about business dynamics saw evidence of declining dynamism (see Decker et al. (2016)). Figure 3 is a graph from the last 40 years, 1979 to 2019, on firm startup rates (see Business Dynamics Statistics (BDS) (census.gov)). What we see is that the firm startup rate has declined from 14% to about 9% There is less entry going on, and that is really important for reallocation.

Equally important to entry itself—we do not want to just see a whole bunch of entry—is whether it is eventually going to be productivity-enhancing reallocation. That is, it is important to know whether "Is the entry a whole bunch of dynamism that doesn't really have much meaning?"

The example I like to give is from a pee-wee soccer game: You look out on the field, there is a whole lot of activity going on. But the activity is not actually accomplishing anything, it is just a lot of churn—a lot of little kids running all over the place.

But what we want to see is a whole lot of activity that actually has meaning. So let us look at businesses in high tech (the green-dotted line) where high tech is defined in a paper by Decker et al. (2020). Even high tech, where we had expected entry that might have a whole lot of meaning, entry has also gone down. There is a negative impact on productivity growth through the entry channel and less efficient reallocation.

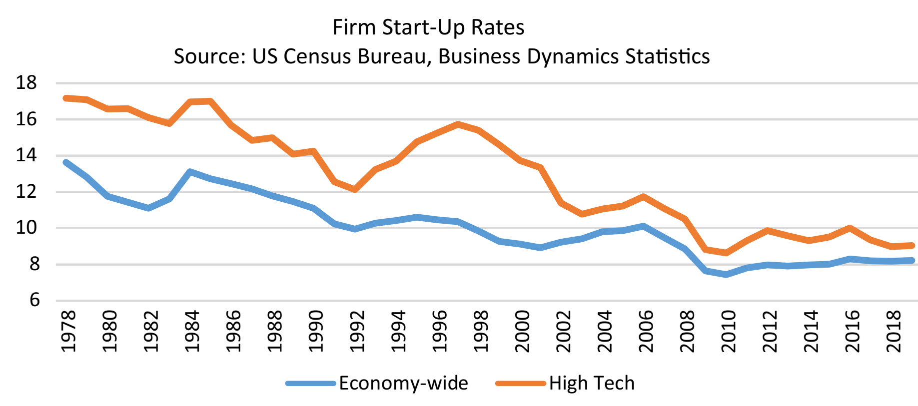
That takes us to where we were at the beginning of the pandemic. Now we have got some information from the Business Formation Statistics, which is a relatively new data product from the Census Bureau (see Business Formation Statistics (census.gov)). These are based on applications for an Employer Identification Number where there is a set of criteria used to filter the data and then a further set of criteria to generate high-propensity business applications.

Now look at what we are seeing for these two series over time in Fig. 4. Together the series capture all business applications, but the ones at the bottom are the ones that have a higher propensity to actually be a business startup. Now, I do not want to say that it is one-for-one correlation between a high-propensity business application and an actual business startup. If you were in John Haltiwanger's talk, you know it is about 30% of high-propensity applications that transition to startups. But this is some promising potential news. Prior to the pandemic—business applications were running about 200,000 a year, and now they are at about 500,000 a year. The open questions here are, "Are these going to transition into businesses?" and "Are they going to turn into businesses that might be transformative?"

Now, the innovation part. I am going to start by talking about the Annual Business Survey from 2019. This covers 300,000 firms, across the U.S. economy in non-agricultural sectors. There are many, many questions in the Annual Business Survey. We were very fortunate to have a module on technology automation and technology adoption in 2019.

The paper by Acemoglu, et al. (2022) using the 2019 Annual Business Survey finds that adoption is low for artificial intelligence (AI) and robotics. From the top row of

Fig. 3 Firm startup rates. *Source* US Census Bureau, Business Dynamics Statistics



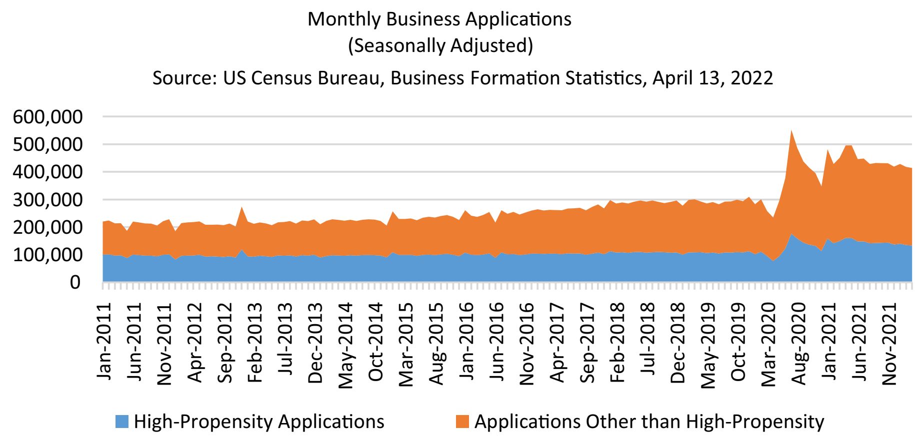


Fig. 4 Monthly business applications. (Seasonally Adjusted). *Source* US Census Bureau, Business Formation Statistics, April 13, 2022

Table 1 Business Innovation

	AI use (%)	Robotics use (%)
Firms	3	2
Worker *Exposure*	13	16
Manufacturing worker *Exposure*	23	45

Source Acemoglu et al. (2022) using the Annual Business Survey 2019

Table 1, you can see AI use is about 3%, robotic use is about 2%. Interestingly, their use is concentrated in larger firms. You can see that the next row down is worker exposure: that is how many workers are in the firms using these technologies. Note the workers are not necessarily "using" the AI or robotics, they are exposed to them in their firm: that is about 13% and 16%, respectively.

Also important is industry. Industry is an important determinant of where these technologies are being adopted. You can see this in the manufacturing worker exposure in the very last line of the table. But I do want to go back and say that another important characteristic with adoption is that if you controlled for firm size, younger is also an important firm characteristic.

Getting to this idea of entry is important, it may be that AI and robotics are adopted by large firms that can handle the high cost of adopting these, and in integrating them. But it also may be that a business is adopting as it enters. So entry is still very important.

Use of these and other technologies collected in the Annual Business Survey 2019 is associated with a 15% increase in productivity (Acemoglu et al. 2022). In terms of this idea about larger firms, which we often think about as "Superstar Firms," or "Frontier Firms," technology presence explains about one-third of the gap between Frontier firms and others. Not in a causal way, but in a deterministic way.

Finally, the last piece of information is from the Small Business Pulse Survey (see Small Business Pulse Survey Data (census.gov)). This is a new survey that the Census Bureau introduced in April 2020. It is 100,000 small businesses surveyed every week with about a 25% response rate.

What I want to highlight here is whereas the technology adoption I was showing in the earlier slide from the Annual Business Survey was concentrated in large firms and in certain industries, and in some sense, it was younger businesses, as well—now I am focusing on small businesses. The results from the Small Business Pulse Survey are closer in timing to the stories that we saw in popular press about businesses pivoting to new ways of doing business during the pandemic. Here, I focus on one question from the Small Business Pulse Survey: "Since March 13th, 2020, has there been an increase in this business's use of online platforms to offer goods and services?"

Figure 5 shows that at the time that we asked this, in summer 2020, the national average of the response of increased online platform use was 25%. But if you look at Sector 61, Educational Services, it was 64%. The open questions here are "How much of this increased platform use is normal?" and "How much of it is going to persist?".

To sum up, using the framework inspired by Gort and Klepper helps us to understand the connection between productivity growth, reallocation, and innovation. Pre-pandemic low entry rates suggest that we might see slower productivity growth to come. But the pandemic surge in applications suggests that there might be higher productivity growth to come.

It is not clear how many of these applications will result in employer businesses, or, moreover, ones that are destined for growth. Innovation hits productivity growth with a lag. Technology adoption has been concentrated in large and/or younger firms. However, the pandemic may have a hastened intensity of adoption and use across a broader set of

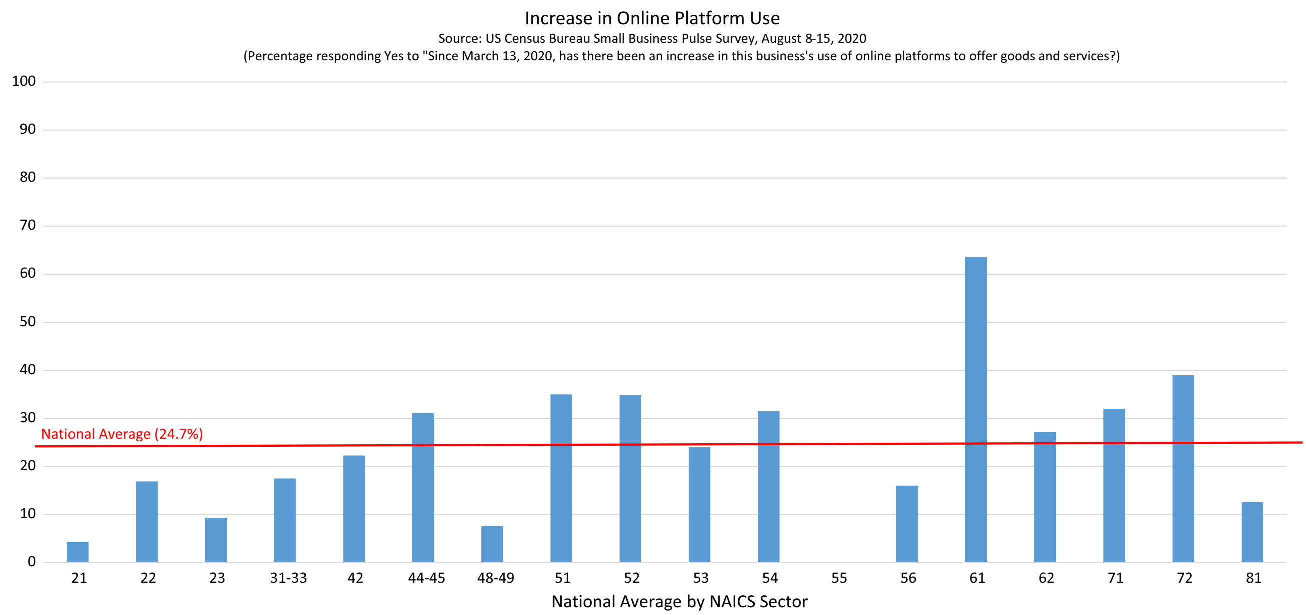


Fig. 5 Increase in online platform use. *Source* US Census Bureau Small Business Pulse Survey, August 8–15, 2020. (Percentage responding Yes to "Since March 13, 2020, has there been an increase in this business's use of online platforms to offer goods and services?)

businesses. It is just not clear how much of this adoption is above normal and permanent. Future work will examine this.

2 ALEX HE

Lucia talked about technology and innovation. I am going to zoom in on a very narrow slice of that question: the productivity effects of artificial intelligence. I will mainly talk about two things.

First, I will present some evidence on how artificial intelligence affects firm-level productivity. This draws on my recent research with Babina et al. (2021) (all the results I will present today are taken from this paper). And then from this evidence, I will talk about some of the potential explanations and thoughts for policy.

Artificial intelligence (AI) is arguably the most important technology of the last decade. There has been a huge explosion in AI investments both by private firms and by governments around the world. The formal definition of an "AI" system is "a machine-based one that can, for a given set of human-defined objectives, make predictions, recommendations, or decisions."

By that definition, the most important AI technologies today are machine learning, natural language processing, and computer vision. All of these technologies can learn from data or experimentation to make predictions or decisions.

There are three key inputs to AI. The first is data, for the algorithms to learn from. The second is computing power to run the algorithms. The third is AI-skilled labor to develop those algorithms. In recent years, there has been a huge accumulation of data, computing is becoming much cheaper than before, and we also have had some methodological breakthroughs in the field of AI. All of these factors led to wider commercial applications of AI technologies.

In our recent work (Babina et al., 2021), we try to measure firms' AI investments using AI-skilled labor, which is one of the three key inputs. The idea is that when firms invest more in AI, they will have more AI-related workers, like machine-learning engineers and data scientists. This is not the only input to AI, but to the extent that AI-skilled labor is complementary to other inputs, firms that invest more in AI will also have more AI-related workers.

We do that by using a unique dataset with hundreds of millions of worker resumes from Cognism Inc. The dataset covers more than 60% of the U.S. workforce in 2018. We analyze the detailed information and description of each job on the resume and look at, for each firm, how many AI-related workers they have at a given point in time. We find that there is indeed a huge increase in AI investments, measured by the share of AI workers (Fig. 6). That increased by more than five times in the last decade.

We also see that the increase in AI investments is ubiquitous across all the industry sectors (Fig. 7). For all industry sectors, we see a large increase in the share of AI workers, and this is not confined to a few narrow industries. This is consistent with the notion that AI is a general purpose technology that can be applied broadly across many industries.

We then look at the impact of AI on firms. We see that, after firms invest in AI, their output grows (Fig. 8). In terms

Fig. 6 Growth in investmetns in artificial intelligence Source: Babina et al. (2021)

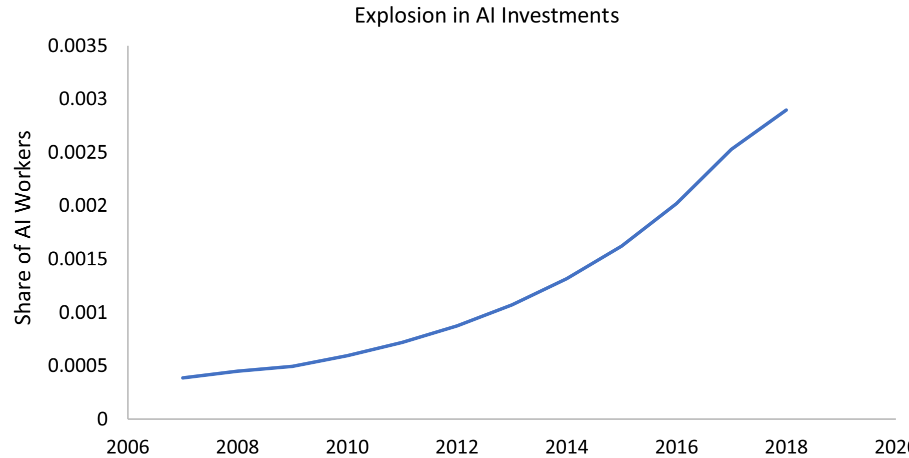


Fig. 7 AI investments by industry Source: Babina et al. (2021)

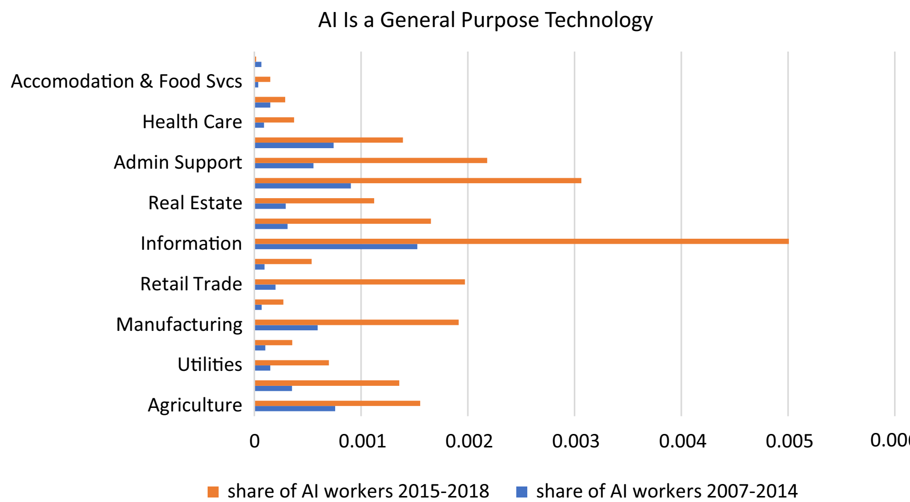
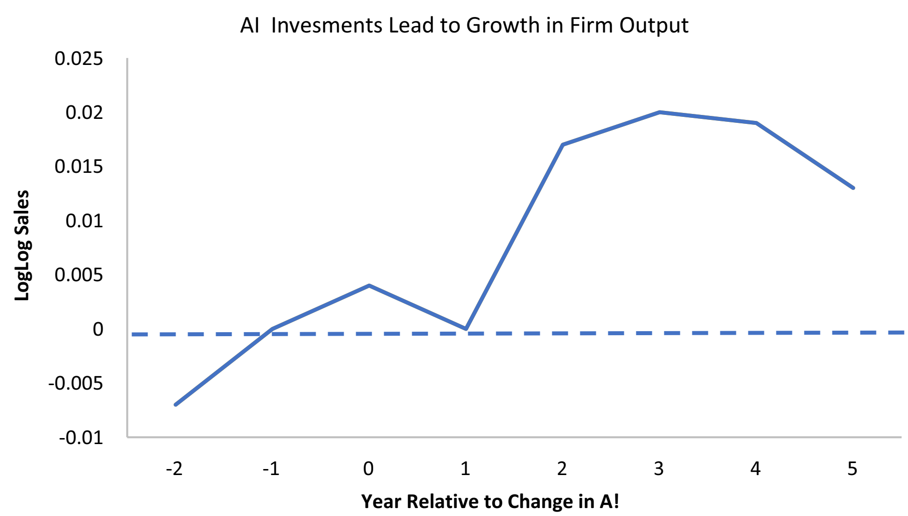


Fig. 8 AI investments and firm output figure Source: Babina et al. (2021)



of the magnitude, a one-standard-deviation increase in AI investments is associated with about 20% higher sales over the time period we look at. That is about 2% or 3% higher growth in sales per year.

However, the growth in sales is not accompanied by higher productivity at the firm level (Table 2). We look at both sales per worker, as a measure of labor productivity, and the revenue TFP. For both measures, we find either a small negative, or zero effect on firm-level productivity.

That is kind of surprising. However, we find that the sales growth is mainly coming from product innovation. We use several measures for product innovation, including trademarks, patents that reflect product innovation as opposed to process innovation, and how much the firm's product portfolios change over time. For all of these three measures, we find a strong positive effect of AI on product innovation (Table 3). That is our first key finding: AI leads to firm growth, but it is mainly from product innovation, not higher productivity.

The second key finding is that the growth effect is concentrated in the largest and most productive firms (Fig. 9), so the benefits from AI are unevenly distributed. This figure shows that the effects on firm growth are monotonically increasing in firm size. We find large positive effects for firms in the largest size tercile, but we do not see any significant effect for the smallest firms (the three bars show from left to right the point estimates for small, medium-sized, and large firms).

Table 2 We find no effect on firm productivity. Source: Babina et al. (2021)

	Change in log sales per worker		Change in revenue TFP	
Change in share of AI workers	− 0.036	− 0.014	− 0.049	− 0.024
	(0.055)	(0.041)	(0.046)	(0.037)
Ind FE	Y	Y	Y	Y
Controls	N	Y	N	Y

*Standard errors in parentheses

**Please note that some numbers differ from the presentation due to updated data

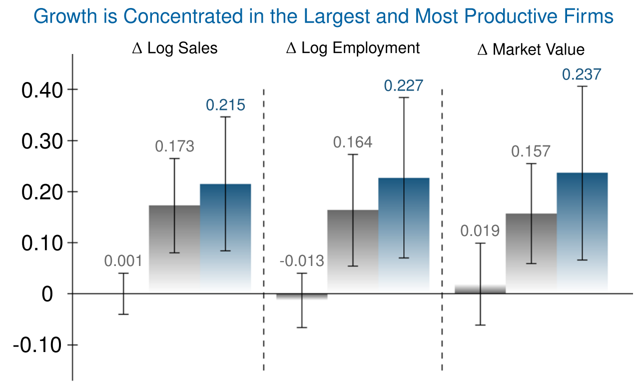


Fig. 9 The effects of AI on growth by firm size. Source: Babina et al. (2021)

To sum up, we find that there is no productivity growth at the firm level, but there is a reallocation to more productive firms at the aggregate level. This is consistent with the "fading stars" story in Gutiérrez and Philippon (2019). They find that the Hulten contribution of productivity growth has declined recently and has been around zero since 2000. Therefore, firms themselves are not becoming more productive per se, but there is a modest increase in productive reallocation when the most productive firms draw more resources toward themselves. I think this is a key piece in the puzzle in explaining the recent low productivity growth. To understand low productivity growth, we really need to understand why firm-level productivity is not rising.

To put this in perspective, when we compare AI to previous general purpose technologies, we see a huge difference in terms of productivity. There are some recent papers either using historical data on electricity (e.g., Fiszbein et al., 2020) or recent data on robots (e.g., Graetz and Michaels, 2018), and they all find positive productivity effects. In terms of IT, there was the Solow paradox in the late 1980s, but then it was followed by rapid productivity growth in the 1990s. Other papers also find similar evidence on AI. A paper by Acemoglu et al. (2022) finds no effect of AI on productivity, but positive productivity effects of other recent technologies, like robots and cloud computing.

What are the potential explanations? There are broadly two views. The first view is that there is just a lag in the

Table 3 But there is a strong positive effect on product innovation. Source: Babina et al. (2021)

	Change in trademarks		Change in product patents		Change in product mix	
Change in share of AI workers	0.144**	0.152**	0.221***	0.229***	0.148***	0.111***
	(0.065)	(0.077)	(0.035)	(0.039)	(0.036)	(0.035)
Ind FE	Y	Y	Y	Y	Y	Y
Controls	N	Y	N	Y	N	Y

*Standard errors in parentheses

**Please note that some numbers differ from the presentation due to updated data productivity growth. We have not seen it yet, but it will come very soon. There is an S curve of technology adoption, and for AI, we are obviously still in the very early stage of adopting the technology. Brynjolfsson et al. (2021) argue that productivity growth follows a J curve, which says that in the early days of technology adoption, firms need to accumulate some intangible capital as complementary inputs to the technology. At this stage, there is not much increase in output. But after the intangible capital is accumulated, we will see output and productivity growth. As a result, we may have an underestimation of productivity growth in the beginning and then an overestimation of productivity growth later. This might be what is going on. But it is not fully consistent what with what we see in the data because we do find that AI leads to a growth in output of firms. We also find no productivity growth even for the early adopters of AI in our sample.

Now, the second view is, "Maybe this time is different." There are some unique features of AI. First, AI has a strong ability to make predictions. This is especially useful for product development and customization. An example is Moderna: A large part of their success in developing a vaccine so fast is that they are using a lot of AI to design the mRNA constructs. Another key feature is that AI relies on big data. This disproportionately benefits larger firms that have more data, either from their operations or from their customers, so that there is a skill advantage to the larger firms in using AI.

In light of these features, there may be a few explanations for why we see that AI-investing firms grow and develop new and better products but fail to improve productivity. First, ideas (on improving productivity) may be getting harder to find (Bloom et al., 2020). This may be especially true for the already very productive firms that are adopting AI.

Second, maybe AI is capable of increasing productivity, but the current efforts of AI are not directed toward that direction. Acemoglu (2021) argues that, currently, when AI is used in the production process, it still mostly focuses on automating human tasks. At this extensive margin, we do not see much productivity growth because AI is not transforming the entire production processes yet. It could also be that due to either entry barriers, regulations, or scale advantages of AI and related technologies, there is declining competition among firms. This could reduce the incentives to improve productivity, and superstar firms may instead grow by expanding their product portfolios, potentially leading to business-stealing effects. In that case, a theoretical paper by Aghion et al. (2019) shows that we may see some temporary productivity gains from reallocation, but in the long run, there will be a decline in productivity because potential new entrants will face the very powerful and efficient firms and may have reduced incentives to innovate and disrupt.

To conclude, AI is happening, and we are seeing an explosion of AI investments in all industries. But the growth of AI is not accompanied by productivity gains at the firm level. We also see that the growth from AI is concentrated in the largest and most productive firms.

One thing to keep in mind is that the adoption of AI is still very low. Lucia's Census survey just showed that only 3% of U.S. firms have adopted AI. In terms of policy, a first step may be to democratize the adoption of AI and address key constraints of AI adoption, like AI-skilled labor and data access, especially for smaller firms. There could also be policies that direct AI more toward productivity improvement, such as targeted R&D subsidies and public–private research partnerships.

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