# THE CONTRIBUTION OF DIGITAL FIRMS TO PRODUCTIVITY GROWTH IN THE MANUFACTURING SECTOR: A DECOMPOSITION APPROACH

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# The contribution of digital firms to productivity growth in the manufacturing sector: A decomposition approach

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**Abstract**

We show that digital and non-digital firms differ significantly with respect to their contribution to productivity growth. Conducting a decomposition analysis on panel data of publicly listed U.S. manufacturing firms covering the 1990-2015 period, we demonstrate that (i) firm-level productivity improvements of digital firms consistently exceed those of non-digital firms; (ii) the market selection process works more efficiently for digital firms; and (iii) the negative correlation between productivity changes and changes in market shares is decisively less pronounced for digital than for non-digital firms. We show that these observed differences in productivity growth can be linked to the idiosyncratic characteristics of digital firms, namely the profound exploitation of digital technologies, the scalability of digital business models and the complementarity of digital and labor investments.

***Keywords:*** Digital firms, industry dynamics, productivity growth, decomposition, labor reallocation
***JEL classification:*** E24, J24, L11, L25, O33, O47

# 1 Introduction

As the global economy transforms from its mechanical, electronic and non-digital origins into a substantial digital form, it is not surprising that also the role of the firm as an economic agent stimulating and sustaining the economic activity has undergone a given transformation (Adner et al., 2019; Barefoot et al., 2018; Teece, 2018). The transition to the 'digital age' has initiated major structural changes which have, in turn, transformed and affected firms' productivity gains. This 'digital age' is commonly defined as the period during which digital firms have emerged and digital technologies – acknowledged as general-purpose technologies (GPTs hereafter) – have spread across all sectors of the economy (Gambardella and Giarratana, 2013; Teece, 2018) promising large productivity gains through higher rates of automation and robotization and improvements in the production process efficiency (Aghion et al., 2017; Anderton et al., 2020). As such, digitalization has fundamentally challenged our understanding of the role of firms in productivity (Goldfarb and Tucker, 2019; OECD, 2020; Van Ark, 2016).

Drawing on the fast rise of digital firms and digital technologies – acknowledged as GPTs driving the 4th Industrial Revolution (EPO, 2021), various micro-data studies have highlighted how digital firms are inherently distinct from non-digital firms with respect to three dominant characteristics which are also crucial for their productivity growth: their resource bundles, their financial/cost structure and their competitive behaviour (Adner et al., 2019; Bajari, 2019). First, digital firms' resource bundles are predominantly characterized by the intensive use of digital resources and technologies (Cusumano et al., 2019; Siebel, 2019). These digital technologies, qualified as GPTs, lie at the core of their economic activity and possess a wide pervasiveness across all industries of the economy and a higher potential of innovation complementarity (Cantner and Vannuccini, 2021; Jovanovic and Rousseau, 2005; Petralia, 2020). Considering these characteristics, the adoption and use of digital technologies can have a clear contribution in the form of large productivity gains at the firm and industry level. Moreover, the nature of the goods and services provided by digital firms may significantly differ compared to those from non-digital firms. On average, digital goods and services are often perceived as more scalable and global than those of non-digital firms. This creates a certain heterogeneity in the goods and services provided across digital and non-digital firms. Second, digital firms have a specific financial/cost structure composed of high fixed and low marginal costs (Adner et al., 2019; Hoffman and Yeh, 2018; Menz et al., 2021). Given the wider applicability of GPTs and the higher fungibility and scalability of their bundle of resources, digital firms, in comparison with non-digital firms, can generate significant economies of scale and scope and benefit from lower costs of adaptation. This facilitates a rapid increase in the size of the respective firm (Agrawal et al., 2018; Autor et al., 2020). The specific financial/cost structure can also favor the creation of high barriers to entry in the industry they are operating in (Aversa et al., 2021; Volberda et al., 2021). Third, digital firms' competitive behavior consists in seeking to occupy a central and dominant position in the market (Korinek et al., 2018; Parker et al., 2021; Teece, 2018). Their behavior is driven by their ambition to quickly establish market power in order to achieve 'winner-take-all' or 'superstar' positions and to benefit from large returns to scale and monopoly advantages (i.e., high margins, higher profit, etc.) (Giustiziero et al., 2021).

In this paper, based on the core argument that digital firms are inherently distinct from non-digital firms, we aim to obtain a clearer understanding of digital firms' overall productivity contribution and of the extent to which it is distributed across the individual components of productivity growth. To do so, we conduct a decomposition analysis following Foster et al. (2001) to separate aggregate productivity growth into firm-level productivity developments, the impact of market share reallocations between firms, and the effect of entering and exiting firms. Moreover, in the course of our decomposition analysis, we explicitly consider the above-mentioned idiosyncratic characteristics of digital firms as the main determinants explaining their respective contribution to productivity.

The basis for our analysis forms a unique sample of U.S. publicly traded manufacturing firms which we constituted for the 1990-2015 period. We use Compustat Segment to create our working definition of digital firms and then merged our sample with CRSP/S&P Compustat databases to obtain firm-level economic and financial information. Following previous studies, we concentrate our analysis on the manufacturing industry (Baldwin et al., 2016; Geurts, 2016; Melitz and Polanec, 2015). The productivity measure deployed in our study is labor productivity, computed as sales per employee. Because we do not observe the use of intermediate goods in our sample, we cannot use value-added which would represent the more preferable output measure. However, to mitigate the drawback of using sales instead of value-added, we conduct our analysis on the rather narrowly defined three-digit sector level where we assume a high correlation between firm-level sales and value-added (see Section 2).

The results of our study can be summarized as follows. We show that (i) firm-level productivity improvements of digital firms consistently exceed those of non-digital firms; (ii) the market selection process, i.e., the reallocation of resources towards the most productive firms works more efficiently for digital firms; and (iii) the negative correlation between productivity changes and changes in market shares is decisively less pronounced for digital than for non-digital firms. We further provide an explanation for how each of these differences in productivity growth can be traced back to the idiosyncratic characteristics of digital firms. As the most essential aspects in this respect, we identify the higher degree in the exploitation of digital technologies, the greater scalability of digital business models and the larger complementarity of digital and labor investments.

Our main contribution to the literature is twofold. First, this paper contributes to the literature on digitalization by advancing knowledge on the implications of the 'digital age' on firms' economic activity (Anderton et al., 2020; Borowiecki et al., 2021; Consolo et al., 2021). Our analysis provides an in-depth understanding and new evidence on the implications of digitalization on economic outcomes, which can explain the ongoing change in market structure. Second, we contribute to the productivity decomposition literature by exploring the specific role of digital firms in aggregate productivity growth and show how this can be linked to their intrinsic digital characteristics. We provide a better understanding on the potential effects of digital firms' idiosyncrasies, more specifically, their digital resources and digital technologies, on productivity growth.

The remainder of this paper is structured as follows. Section 2 presents our definition of digital firms and describes our data. Section 3 introduces the decomposition method deployed in our analysis. In Section 4, we present our empirical results and analysis. Section 5 concludes.

## 2 Data

This paper is based upon the Compustat Segment and CRSP (Center for Research in Securities Prices)/S&P (Standard & Poor) Compustat database. The data set contains information on publicly listed U.S. digital and non-digital firms over the 1990-2015 period.[1] We compose this sample following a two-step procedure: in the first step, we formulate our working definition of a digital firm using Compustat Segment. Following Deperi et al. (2022), we define digital firms as firms generating at least fifty percent of their sales that stem from segments identified as digital. We choose to fix the threshold of the total value created on digital segments to 50 percent because we aim at identifying firms that heavily participate and operate on digital industry segments. Therefore, we calculate the sum of total sales achieved on segments identified as digital for each firm. We rely on two different and independent digital industry taxonomies to determine digital industry segments: the digital industry taxonomy of Barefoot et al. (2018) from the Bureau of Economic Analysis and from ONS (2015), the Office of National Statistics[2].

In the second step, we collect firm-level financial statements from the CRSP/S&P Compustat database to obtain information on firm identifiers, year of reporting, firms' NAICS two-digit and three-digit code (North American Industry Classification System, 2017), annual total sales and employment. In line with previous studies, we are considering manufacturing firms exclusively, focusing on the 33 NAICS two-digit sector over the period under study, because it is the only two-digit manufacturing sector that includes a relevant number of digital firms needed to conduct our study. Moreover, we choose to concentrate our analysis exclusively on U.S. public firms operating in this sector for two main reasons. First, we include in our sample only public firms to guarantee the availability and accuracy of the information collected. Second, the U.S. offer a large-scale dynamic environment with the significant emergence and presence of digital firms throughout the years. The U.S. is admittedly seen as the leader in the adoption and application of digital technologies and relies heavily on the exploitation and development of these technologies (Barefoot et al., 2018; IMF, 2018). In Table 1, we report summary statistics of our sample.

As shown in Table 1, we decide to focus on three different time periods, each with its individual formative events and characteristic features which we will refer back to in our empirical analysis in Section 4. The first period, from 1990 to 2000, corresponds to the nascent spread of information and communication technologies (ICTs). The second period, from 2001 to 2007, has known a significant internet crisis with a peak in 2002 while the ICTs kept spreading throughout specific sectors of the economy (i.e., in sector 51 predominantly). The third period, from 2008 to 2015, began with a profound financial turmoil and a worldwide instability. However, following this downturn, it was the beginning of a new era with the emergence of major digital players and large-scale digital projects. The post-crisis period is often associated with the advent of the 'Digital Age' and the spread of artificial intelligence (AI) amongst other digital technologies (i.e. blockchain, machine learning, cloud computing, etc.) and ICTs throughout the economy.

Our dataset represents an unbalanced panel. Since it comprises publicly listed firms, new firms generally enter the database in the form of an initial public offering of their company shares,

[1] We restrict our sample to this specific period in order to reflect the emergence of the internet and the web.
[2] This institution is part of the Organisation for Economic Cooperation and Development (OECD).

Table 1: Summary statistics for publicly listed manufacturing firms.

| | | Count | Mean | SD | p5 | p95 |
|---|---|---|---|---|---|---|
| 1990-2000 | | | | | | |
| Digital firms | Sales | 3,685 | 473,565 | 3,146,727 | 1,398 | 1,241,687 |
| | Employment | 3,685 | 3,096 | 11,856 | 34 | 11,167 |
| | Labor productivity | 3,685 | 147 | 400 | 15 | 452 |
| Non-digital firms | Sales | 8,712 | 1,826,172 | 9,625,931 | 2,195 | 6,604,475 |
| | Employment | 8,712 | 6,480 | 30,519 | 31 | 23,900 |
| | Labor productivity | 8,712 | 305 | 871 | 29 | 897 |
| 2001-2007 | | | | | | |
| Digital firms | Sales | 2,518 | 981,051 | 5,679,548 | 3,746 | 2,807,602 |
| | Employment | 2,518 | 3,673 | 12,480 | 33 | 17,097 |
| | Labor productivity | 2,518 | 291 | 487 | 27 | 850 |
| Non-digital firms | Sales | 4,932 | 1,898,504 | 9,817,880 | 2,704 | 6,962,943 |
| | Employment | 4,932 | 6,797 | 23,986 | 30 | 26,634 |
| | Labor productivity | 4,932 | 279 | 419 | 28 | 796 |
| 2008-2015 | | | | | | |
| Digital firms | Sales | 2,013 | 1,351,372 | 8,709,023 | 3,580 | 4,067,947 |
| | Employment | 2,013 | 5,487 | 21,017 | 26 | 24,500 |
| | Labor productivity | 2,013 | 339 | 479 | 26 | 1,021 |
| Non-digital firms | Sales | 3,919 | 2,326,179 | 11,202,625 | 2,443 | 8,261,919 |
| | Employment | 3,919 | 8,851 | 25,896 | 29 | 36,700 |
| | Labor productivity | 3,919 | 238 | 310 | 24 | 602 |

*Notes*: The table depicts summary statistics for digital and non-digital firms within the manufacturing sector (NAICS 33) during the three time periods considered in our study. All values are reported for the cleaned sample as documented in Section 2. Sales are reported in thousand deflated US$, productivity is measured in thousand deflated US$ per employee. SD is the standard deviation, p5 and p95 describe the 5th and 95th percentile of the distribution, respectively.

while exits are caused by a delisting of shares. Note that newly listed firms may encompass recently founded firms which have then gone public while it also includes more mature companies which have decided to publicly list (segments of) their company. Furthermore, a delisting of shares does not necessarily imply a company's closure. Instead, the company may have been part of a merger or may have simply transferred its shares into private ownership.

Another consequence of investigating publicly listed firms is that we deal with a strongly fat-tailed distribution of firm sizes. As depicted in the 'granular hypothesis' by Gabaix (2011), the aggregate development of such fat-tailed industries may be substantially shaped by idiosyncratic shocks to large firms. For our analysis, we deliberately kept these large firms in the database. Our underlying hypothesis is that digital industries are particularly dominated by a small number of large firms as digital business models typically lead to winner-take-all situations, as explained in Section 1. Hence, ignoring these large players when comparing digital and non-digital firms would be tantamount to ignoring an essential characteristic and consequence of the digital age. Nonetheless, when interpreting the decomposition results, it may be that the differences between the two groups are mainly driven by the fat tail. Therefore, any attempt of generalizing our findings for all digital and non-digital firms, independent of their market position, may be inadequate. To address this issue, we also conducted our decomposition exercise when trimming the largest percentile of firms with respect to sales.[3] While the comparisons we draw between digital and non-digital firms mostly hold when excluding the largest percentile, we do observe a significant impact of the largest firms on the overall productivity development. This is in particular the case during the periods from 2001-2007 and 2008-2015. We explicitly point out this impact in our empirical analysis in Section 4.

To construct our productivity index, we use sales as our output and labor as our input measure. Because we do not observe prices, we deflate firm-level sales using gross output deflators on the four-digit industry level, provided by the U.S. Bureau of Economic Analysis. We have no information on the value-added of firms in our dataset, which would take the use of intermediate goods into consideration and would thus represent a better output measure when comparing firms with different production processes. However, previous studies have shown a high correlation between firm-level gross output and value-added within narrowly defined industries (see e.g. Foster et al., 2001; Bartelsman et al., 2013). Since we conduct our decomposition analysis on the rather narrowly defined NAICS three-digit industry level (see Section 3), sales can be assumed to represent a valid output measure for the purpose of our study.[4] A list of the three-digit industries included in our dataset can be found in Table 3 in Appendix A. We treat the presence of extreme values in productivity growth in our dataset by trimming annual firm-level productivity growth at the 1st and 99th percentile. Furthermore, we only include firms that consistently reported positive values for sales and employees. Subsequently, to ensure reliable decomposition results, we only keep three-digit sectors with at least 30 firms in each reporting year of the period under investigation.

# 3 Methodology

## 3.1 Productivity decomposition

The central idea of productivity decomposition consists in providing insights into the micro-level sources of aggregate productivity developments. These sources generally include firm-level productivity improvements, the reallocation of resources between firms with different productivity levels and firm turnover. The most commonly used methods for decomposing productivity growth are the ones proposed by Griliches and Regev (1995), Foster et al. (2001) and Melitz and Polanec (2015). While the former two are time-series approaches derived from the seminal contribution by Baily et al. (1992), the latter may be seen as a dynamic extension of the cross-sectional methodology by Olley and Pakes (1996). In spite of several methodological differences, all three methods serve the same conceptual purpose of shedding light on the above-mentioned sources of aggregate productivity growth. Supported by the increasing availability of firm-level data, they have been applied in numerous studies across different countries, industries, and time

[3]To better grasp the scale of the firms affected by this trimming, note that they include digital firms such as Apple, HP and Dell Technologies and non-digital firms such as General Motors, Ford Motors and Boeing.

[4]Nonetheless, note that using sales may induce an underestimation of digital firms' productivity compared to non-digital firms due to their generally different value chains. Previous studies have shown that digital firms' value chains rely less on intermediate goods (Cardona et al., 2013; Kretschmer, 2012), implying that the value-added of digital firms relative to their sales is larger than for non-digital firms. However, we expect this bias to have only a minor impact on our results, as it can induce either an underestimation or overestimation of firms' productivity growth components, depending on whether a respective firm's productivity is above or below the industry average and whether this firm increases or decreases its productivity. Therefore, we expect a balancing of this bias.

spans.[5]

For our analysis, we use the decomposition proposed by Foster et al. (2001). We deliberately opt for this method for two reasons. First, it allows for a detailed investigation of the productivity contributions of market share reallocations, separating a static and a dynamic component, as we explain below. This constitutes a considerable advantage over the two frequently used alternative decomposition methods by Griliches and Regev (1995) and by Melitz and Polanec (2015), which do not clearly disentangle the productivity effects of market share changes from those of productivity changes. As we show in our empirical application in Section 4, the separation of these two effects offers fundamental insights into the industry dynamics underlying aggregate productivity movements, thus reinforcing our choice of decomposition method. Second, compared to the cross-sectional approach used in the more recent decomposition method by Melitz and Polanec (2015), the time series approach in the decomposition method by Foster et al. (2001) facilitates the separate analysis of digital and non-digital firms' contribution. In contrast to the cross-sectional method which is essentially based on an unweighted productivity average and a covariance term, the time series approach tracks and weighs each firm's growth contribution individually. This allows to segment aggregate productivity growth in the manufacturing sector into the contributions of digital and non-digital firms, and to illustrate the overall role digital firms play compared to non-digital firms with respect to manufacturing-wide productivity developments.

In a first step, the productivity decomposition proposed by Foster et al. (2001) breaks down aggregate productivity growth into the contributions of surviving (S), entering (E), and exiting firms (X). The contribution of surviving firms can then be further decomposed into three subcomponents, which they label the within-firm effect, the between-firm effect, and the cross-firm effect:

$$\begin{aligned}\frac{\Phi_2-\Phi_1}{\Phi_1} = \frac{1}{\Phi_1}\cdot\Big[&\sum_{i\in S} s_{i1}\cdot\triangle\varphi_i + \sum_{i\in S}\triangle s_i\cdot(\varphi_{i1}-\Phi_1) + \sum_{i\in S}\triangle s_i\cdot\triangle\varphi_i \\ &+\sum_{i\in E} s_{i2}\cdot(\varphi_{i2}-\Phi_1) + \sum_{i\in X} s_{i1}\cdot(\Phi_1-\varphi_{i1})\Big]\end{aligned} \tag{1}$$

where $\Phi_1$ and $\Phi_2$ denote aggregate productivity in two successive years, $\varphi_{i1}$ indicates the initial productivity and $s_{i1}$ the initial market share of firm $i$. As is common when using labor productivity, we use labor weights, that is, the number of employees, as market shares. The differences in firm-level productivity and shares over the respective period are represented by $\triangle\varphi_i$ and $\triangle s_i$, respectively.

The first sum on the right-hand side of Equation 1 depicts the within-firm effect. It reflects the aggregate productivity contributions of efficiency improvements on the individual firm level, while isolating any contributions caused by changes in firms' market shares. The between-firm component, which constitutes the second sum, represents the opposite case, holding the productivity measure constant and capturing productivity contributions due to changes in shares. A positive between-firm effect indicates that market shares are generally reallocated from the

[5] For a brief overview of decomposition methods and studies, consider the review by Krüger (2008). As more recent contributions conducting decomposition exercises, consider, for instance, the studies by Bartelsman et al. (2013); Melitz and Polanec (2015); Decker et al. (2017); Brown et al. (2018); Dias and Marques (2021).

less to the more productive firms within the industry, which positively contributes to aggregate growth.[6] As the third and last component of surviving firms, the cross-firm effect reflects an interaction component of the previous two. It provides a statement on how changes in productivity are associated with changes in market shares. Due to the fact that both the between- and the cross-firm effect involve market share changes, one may regard the sum of the two as the total impact of labor reallocation between firms. We will refer to this aggregate as the 'reallocation component' in Section 4, with the between component as the 'static' and the cross component as the 'dynamic' reallocation component. The impact of industry churning on productivity growth is captured by the last two sums in Equation 1. The two components depict the contributions of entering and exiting firms, respectively, weighted by their individual shares.

### 3.2 Decomposing productivity growth of digital and non-digital firms

Apart from investigating the decomposed productivity components on a country-, industry- or time-specific level, some decomposition studies go one level deeper and analyze whether the productivity components differ among certain groups of firms that share similar firm-level characteristics. For instance, Baily et al. (1996) cluster firms into four different groups depending on the development of their productivity and employment and investigate how the decomposed productivity contributions differ among these groups. As another example, consider Grebel et al. (2022) who find that the decomposed productivity components vary substantially between different firm sizes and export intensities. A firm-level characteristic which, to the best of our knowledge, has so far not been investigated with respect to its manifestation in decomposed productivity, is the classification of digital and non-digital firms. Given their very distinct firm-level features, as explained in the introduction, we expect significant differences in the productivity components of digital and non-digital firms.

To compute the productivity contributions of the two separate groups of digital and non-digital firms, we follow a two-step procedure. In a first step, we compute the productivity decomposition by Foster et al. (2001) for annual growth rates in each of the three-digit manufacturing industries within our dataset, while tracking the contributions of firms according to their status, digital or non-digital.[7] For weighing digital and non-digital firms' contributions, we use their respective labor share in aggregate employment of the entire three-digit manufacturing industry. This ensures that, in sum, the contributions of digital and non-digital firms result in aggregate productivity growth of the respective three-digit manufacturing industry, as shown in Equation 2:

[6] Evidently, to accurately estimate the productivity impact of shifting resources towards the more productive firms requires the observation of marginal productivity on the firm level. Since this is not the case, we rely, as in all linear decomposition methods, on the assumption of constant returns to scale, i.e., that an increase in market shares will lead to a linear increase in output and assume this to be a close enough approximation.

[7] If a firm changes its status from one year to another, we exclude the corresponding annual growth contribution in order to achieve a clear cut differentiation between digital and non-digital firms' contributions.

$$
\begin{aligned}
\frac{\Phi_{j2}-\Phi_{j1}}{\Phi_{j1}} = \frac{1}{\Phi_{j1}} \cdot \Big[ & \sum_{i\in S_{Dj}} s_{i1}\cdot \triangle\varphi_i + \sum_{i\in S_{Dj}} \triangle s_i \cdot (\varphi_{i1}-\Phi_{j1}) + \sum_{i\in S_{Dj}} \triangle s_i \cdot \triangle\varphi_i \\
& + \sum_{i\in E_{Dj}} s_{i2}\cdot(\varphi_{i2}-\Phi_{j1}) + \sum_{i\in X_{Dj}} s_{i1}\cdot(\Phi_{j1}-\varphi_{i1}) \\
& + \sum_{i\in S_{Nj}} s_{i1}\cdot \triangle\varphi_i + \sum_{i\in S_{Nj}} \triangle s_i \cdot (\varphi_{i1}-\Phi_{j1}) + \sum_{i\in S_{Nj}} \triangle s_i \cdot \triangle\varphi_i \\
& + \sum_{i\in E_{Nj}} s_{i2}\cdot(\varphi_{i2}-\Phi_{j1}) + \sum_{i\in X_{Nj}} s_{i1}\cdot(\Phi_{j1}-\varphi_{i1}) \Big]
\end{aligned} \tag{2}
$$

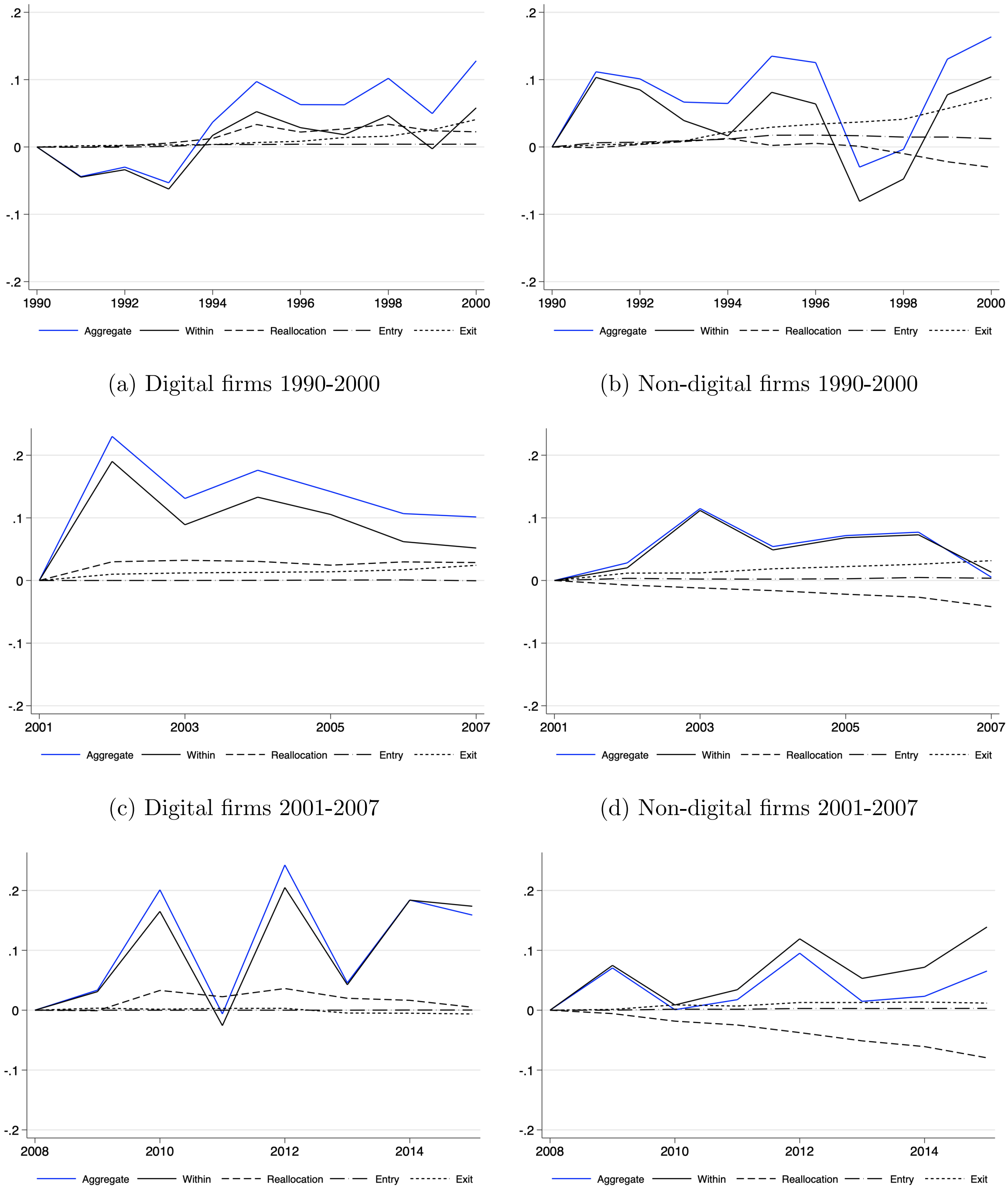
where $\Phi_{j1}$ and $\Phi_{j2}$ denote aggregate productivity in three-digit industry $j$ in two successive years, $S_{Dj}$, $E_{Dj}$ and $X_{Dj}$ represent the groups of surviving, entering and exiting *digital* firms in industry $j$, respectively, while $S_{Nj}$, $E_{Nj}$ and $X_{Nj}$ denote the corresponding groups for *non-digital* firms.

In a second step, we aggregate the three-digit industry results to the two-digit level to construct the average manufacturing industry, again differentiating between digital and non-digital firms. To compute the average manufacturing industry, we use three-digit industry employment as weights, averaged over the beginning and ending years of the period in which the respective growth rate was measured.

## 4 Empirical application

We conduct our decomposition analysis using a panel data set covering the U.S. manufacturing sector for three specific time periods, namely for 1990-2000, 2001-2007 and 2008-2015. As discussed in Section 2, the data represents a right-skewed distribution which requires close attention to the impact of the largest firms. Since the phenomenon of a small number of dominating firms is an essential characteristic of many industries and especially of digital industries, we deliberately include these firms in our main analysis. Nonetheless, when drawing comparisons between digital and non-digital firms, we will indicate how our observations are shaped by these large firms. For computing the productivity contributions of digital and non-digital firms, we follow the procedure shown in Section 3. Our results are illustrated in Figure 1 and Table 2, respectively. In Figure 1, we plot the accumulated annual values for each component of the productivity decomposition, allowing us to track the components' development over time and at the same time retrieve their accumulated contribution over the three periods under consideration. For the illustration in Figure 1, we combine the between- and cross-firm effect in a reallocation component in order to capture the total productivity contribution of changes in market shares in a single measure (as done by Caselli et al., 2021). However, as we will show, the separate observation of the between- and the cross-firm components provides further valuable insights. We illustrate their separate impact in the form of averages of annual productivity contributions in Table 2. The table further depicts productivity contributions *per firm*. Due to the pronounced skewness in the firm distribution (see Section 2), these average values can be expected to be strongly influenced by the largest and most productive firms. Nonetheless, since the digital and non-digital classifications contain different numbers of firms, they offer a useful orientation and enable a more direct comparison of the individual contribution of the average digital and non-digital firm.

Figure 1: Accumulated productivity contributions of digital and non-digital manufacturing firms.




(a) Digital firms 1990-2000

(b) Non-digital firms 1990-2000

(c) Digital firms 2001-2007

(d) Non-digital firms 2001-2007

(e) Digital firms 2008-2015

(f) Non-digital firms 2008-2015

## 4.1 Development of aggregate productivity

Before we investigate the contribution of the individual productivity components, we briefly outline the development of aggregate productivity over the three time-periods under consideration. Within each of the three time-periods, we observe an overall increase in aggregate productivity. However, both for digital and for non-digital firms, aggregate growth undergoes substantial fluctuations, with each period containing years with significantly negative as well as positive growth rates (see Figure 1). Considering the average growth rate of all firms in our sample, that is, digital and non-digital firms, Table 2 reveals a slowdown in the rate from initially 3.12% between 1990 and 2000 to 2.3% in the second period, before almost doubling to an average rate of 4.29% in the last period. As shown in the table, the intermediate slowdown in productivity growth is caused by the slump in the contribution of non-digital firms between 2001 and 2007, while digital firms demonstrate a steady increase in their average growth contribution. Except for the first period, digital firms' aggregate productivity growth exceeds that of non-digital firms, both in view of the accumulated values in Figure 1 and of the average contributions in Table 2. With respect to aggregate growth rates *per firm* depicted in Table 2, the differences become even more pronounced, with digital firms consistently surpassing non-digital firms. Moreover, we observe a more than threefold increase for digital firms' *per firm* contribution between the first and the last period, while, for the average non-digital firm, the contribution is roughly equal for the first and the last period, after being almost zero during the 2001-2007 period. Note that the comparisons drawn for aggregate growth are strongly driven by the largest firms in our sample, with their impact increasing over time. This especially affects the group of digital firms, which is in line with our hypothesis that the tendency towards concentration and winner-take-all situations is stronger in digital industries.[8]

Table 2: Productivity contributions of digital and non-digital firms in the manufacturing sector.

| Period | Status | #Incumbents | #Entries | #Exits | Aggr | Within | Between | Cross | Entry | Exit |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | *per firm* | | | | | |
| 1990-2000 | digital | 313 | 8 | 23 | 1.33 | 0.66 | 0.87 | -0.64 | 0.04 | 0.40 |
| | | | | | *0.0041* | *0.0021* | *0.0028* | *-0.0020* | *0.0050* | *0.0173* |
| | non-digital | 754 | 20 | 47 | 1.79 | 1.27 | 1.99 | -2.29 | 0.12 | 0.71 |
| | | | | | *0.0023* | *0.0017* | *0.0026* | *-0.0030* | *0.0061* | *0.0150* |
| | all | 1068 | 71 | 29 | 3.12 | 1.92 | 2.86 | -2.94 | 0.17 | 1.11 |
| | | | | | *0.0028* | *0.0018* | *0.0027* | *-0.0027* | *0.0057* | *0.0158* |
| 2001-2007 | digital | 339 | 3 | 26 | 2.08 | 1.21 | 0.78 | -0.30 | -0.01 | 0.40 |
| | | | | | *0.0059* | *0.0036* | *0.0023* | *-0.0009* | *-0.0020* | *0.0152* |
| | non-digital | 670 | 7 | 49 | 0.22 | 0.34 | 0.93 | -1.63 | 0.06 | 0.52 |
| | | | | | *0.0003* | *0.0005* | *0.0014* | *-0.0024* | *0.0089* | *0.0106* |
| | all | 1009 | 75 | 10 | 2.30 | 1.55 | 1.70 | -1.93 | 0.05 | 0.92 |
| | | | | | *0.0022* | *0.0015* | *0.0017* | *-0.0019* | *0.0055* | *0.0122* |
| 2008-2015 | digital | 235 | 2 | 21 | 3.23 | 3.23 | 0.52 | -0.44 | 0.004 | -0.09 |
| | | | | | *0.0130* | *0.0138* | *0.0022* | *-0.0019* | *0.0016* | *-0.0042* |
| | non-digital | 467 | 7 | 28 | 1.07 | 2.03 | 0.16 | -1.34 | 0.04 | 0.17 |
| | | | | | *0.0022* | *0.0043* | *0.0004* | *-0.0029* | *0.0061* | *0.0060* |
| | all | 702 | 49 | 9 | 4.29 | 5.26 | 0.69 | -1.78 | 0.05 | 0.08 |
| | | | | | *0.0059* | *0.0075* | *0.0010* | *-0.0025* | *0.0049* | *0.0016* |

*Notes*: The table depicts firm counts and productivity contributions of firms within the manufacturing sector (NAICS 33) according to their status during the three time periods considered in our study. All values are unweighted averages of annual results for the weighted manufacturing industry. Productivity contributions are in percent. Values in italics represent productivity contributions in percent divided by the average number of firms within the industry (for Aggr), of incumbents (for Within, Between and Cross), of entries (for Entry) and of exits (for Exit), respectively.

When looking at the general breakdown of aggregate productivity growth into its components in Figure 1, it becomes clear that the mentioned fluctuations as well as the overall development of aggregate growth are dominated by the within-firm effect. This predominance of the within-firm effect is in line with the findings of previous decomposition studies (see e.g. Foster et al., 2001;

[8]When excluding the largest percentile of firms, accumulated aggregate growth in the second period is about equal for digital and non-digital firms. During the third period, it even turns negative and becomes smaller for digital than for non-digital firms.

Brown et al., 2018; Caselli et al., 2021). Hence, firm-level efficiency changes rather than productivity contributions associated with changes in market shares shape aggregate productivity movements in our sample. Note that the relatively small values for the within-firm component in Table 2, which seem to contradict this finding, are due to the fact that the values in the table represent time averages, which balance the large fluctuations of the within-firm component. Further note that the opposed sign of the relatively large average contributions of the between- and cross-firm effects in Table 2, which capture productivity contributions associated with market share changes, cause the relatively small reallocation component in Figure 1. We further comment on this below.

### 4.2 Productivity contribution of firm-level productivity changes

As explained in Section 3, the within-firm effect offers insights into the aggregate impact of firm-level efficiency developments by controlling for changes in firms' market shares. Despite the mentioned large fluctuations in the within-firm component of both digital and non-digital firms, there is an overall positive accumulated contribution within each period (see Figure 1). With the exception of the period from 1990 to 2000, we observe a larger within-firm component for digital than for non-digital firms. In analogy to our findings for aggregate productivity growth, the overall positive within-firm components are strongly shaped by the largest firms, implying that the major share of efficiency improvements can be attributed to them. Once again, this phenomenon is more pronounced for digital firms, which confirms the winner-take-all character of digital industries.[9]

At the outset of the first period, the accumulated within-firm component of digital firms is negative before experiencing a substantial increase between 1993 and 1995, which initiates an overall positive trend. This observation may be linked to the fact that the digital industry is still a nascent industry at that time. Indeed, at the beginning of this first period, new players are evolving in a still very unstable and not clearly structured industry. During these years, digital firms pursue their preliminary investments and exploitation of ICTs. With the evolution of time and a better structuring of the industry, the digital incumbents start to benefit from their investments in ICT- and digital-based goods and services (Becchetti et al., 2003; Consolo et al., 2021; Sharpe et al., 2006).

The reaping of these benefits is particularly visible in the second time period considered in our study, that is, in the beginning of the 2000s, where we observe a significant upward spike in digital firms' productivity by almost 20% between 2001 and 2002, which is consistent with the trend of the previous period. However, the years 2004 to 2007 demonstrate a significant decrease of the within-firm effect of digital firms. These years correspond to the emergence of AI and its early adoption, which, as a rising new technology, requires a certain degree of adaptations and modifications at the firm-level which can affect firms' productivity. Hence, the mentioned slump in productivity between 2004 and 2007 may be linked to the time lag that firms operating in this industry need before collecting the benefits of their investments in AI (Anderton et al., 2020; Cardona et al., 2013; Conway, 2017). Non-digital firms also experience a spike and subsequent slump in productivity in the beginning of the 2000s, but less pronounced than for digital firms.

[9] When trimming the largest percentile, the within-firm component of digital firms exceeds that of non-digital firms in the first and second period, but becomes negative and smaller than for non-digital firms in the last period.

In the ensuing years, firm-level productivity of non-digital firms slightly increases before sharply decreasing between 2006 and 2007, marking the beginning of the financial crisis.

For the last period under study, we observe large fluctuations of the within-firm component of digital firms that even cause a negative accumulated contribution of around -2% in 2011. Still, the overall accumulated contribution in 2015 is strongly positive at almost 20%. The overall positive within-firm component as well as the intensity of the fluctuations can be largely explained by the respective contributions of two major players in the digital industry, namely of Apple (2010-2013) and HP (2014), who undergo substantial increases and decreases in sales during these years. Nonetheless, even when controlling for the impact of the largest players, the within-firm component fluctuates between positive and negative contributions during the 2008-2015 period. We may relate these fluctuations to a further evolution of technology and the emergence and adoption of digital technologies such as cloud computing, the blockchain, machine learning, or the internet of things (IoT) (Evangelista et al., 2014; Pells, 2018; Qu et al., 2017). The diffusion and adoption of these digital technologies is associated with firm-level productivity gains through digital innovation, improvement of business efficiency, and investments in complementary assets and labor (Sorbe et al., 2018; Borowiecki et al., 2021). However, these productivity gains are typically not of a constant nature. There are some firms' organization practices and decisions on resource allocations that can alter reaping the full benefits of new digital technologies, which can lead to a large divergence in firm-level productivity and growth rates within the industry (Bartelsman et al., 2013; Bloom and Van Reenen, 2010; Calvino et al., 2018). Concerning the development of non-digital firms during the last period, in contrast, we can observe a rather steady and more moderate increase in productivity, interrupted only by smaller decreases in 2010 and 2013, culminating in an overall within-firm effect of roughly 13% in 2015. This more steady development is in line with the fact that non-digital firms are less exposed to the aforementioned disruptions caused by digital technologies.

Regarding the productivity contributions *per firm*, Table 2 shows that digital firms' within-firm effect consistently exceeds that of non-digital firms, which is particularly visible in the later two periods. In fact, between 2001 and 2007, the average digital firm's contribution is as much as seven times the size of non-digital firms and is still more than three times as large between 2008 and 2015. Since the average non-digital firm in our dataset is between 1.6 (2008-2015) to 2 (1990-2000) times larger than the average digital firm, the gap between their average contribution becomes even more profound when measuring the average within-firm component per employee. In line with our explanations above, the driving force of these high firm-level efficiency improvements of digital firms are the largest players that manage to exploit their dominating position to further increase their sales per employee.

To sum up, since the beginning of the 2000s, digital firms play a clearly dominating role in the overall within-firm contribution to aggregate productivity growth. We further observe a substantially and consistently higher degree of firm-level efficiency improvements in digital firms, which is also in line with the literature (Anderton et al., 2020; Dhyne et al., 2018; OECD, 2021). As explained above, we posit that these productivity gains are rooted in digital firms' exploitation of ICTs and digital technologies, their intrinsic characteristics and their specific cost/financial structure (Borowiecki et al., 2021; Cette et al., 2021; Kretschmer, 2012).

### 4.3 Productivity contribution associated with resource reallocation

With respect to the reallocation component, which encompasses the between- and cross-firm effect and thereby all productivity developments associated with changes in market shares, the differences between digital and non-digital firms are even more pronounced than for the within-firm component. As shown in Figure 1, for each of the three periods, the accumulated impact of the reallocation component is positive for digital and negative for non-digital firms. The positive reallocation component of digital firms can be primarily traced back to the positive contributions of the largest digital players. This confirms our expectation that the already large digital firms tend to expand their market shares even further due to the very pronounced winner-take-all characteristic of digital business models.[10] Hence, as a first insight, we can derive that the overall resource reallocation process generally works in a productivity-enhancing way for digital firms, while being counter-productive for non-digital firms. However, when separating the reallocation component into its constituent parts, that is, into a between- and a cross-firm component, a more differentiated picture is revealed.

**Productivity contribution of the between-firm component**

The between-firm component, i.e., the static reallocation component holding the productivity measure constant, is, on average, positive for digital as well as for non-digital firms during each of the three periods under consideration (see Table 2). Overall, this implies a well-working market selection process: the more productive firms tend to increase their market share while the less productive firms tend to shrink in size, which both contributes positively to aggregate productivity. However, comparing the contributions *per firm* reveals that the between component for digital firms is consistently larger than for non-digital firms, with the gap between the two groups of firms increasing over time.

This gap in the efficiency of allocating resources towards the most productive firms can possibly be explained by the specificity of digitally driven business models. Digital firms seek to occupy a central position on the market and to become 'superstars' in order to thrive in a fast-evolving environment (Adner et al., 2019; Porter and Heppelmann, 2014). This competitive approach leads to a rise of market concentration and winner-take-all situations of the most productive firms (Evens and Donders, 2018; Iansiti and Lakhani, 2017; Tiwana, 2013). Less productive digital firms, on the other hand, tend to shrink in such an environment due to their lack of capacity and agility to adapt and survive (Zhu and Iansiti, 2019; Van Alstyne et al., 2016). The higher between-firm effect of digital firms might also be explained by the fact that digital firms are generally able to generate more significant economies of scale through the exploitation of their productive resources compared to non-digital firms (Adner et al., 2019; Autor et al., 2020). In addition, digital firms are more likely to benefit from a decrease of both their production and distribution costs over time due to the high scalability of their resource bundles (Hoffman and Yeh, 2018). Finally, digital firms have the possibility to benefit from strong network effects which are relatively specific to the digital industry (Parker and Van Alstyne, 2005). Network

[10] If we exclude the largest percentile of firms, the accumulated reallocation component is still higher for digital than for non-digital firms. However, it also turns negative for digital firms in the second and third period, as an exclusion of the largest players leads to a less positive between-firm and more negative cross-firm component. We provide more details regarding the underlying mechanisms in the main text.

effects refer to (i) a return-to-scale effect indicating that the value of a network increases as the number of users within the network increases, and (ii) a productivity effect resulting from innovative adoptions and adaptations of, for instance, digital technologies (Kretschmer, 2012; Tiwana, 2013). Due to their higher capacity to quickly reach a larger scale and attract more users, it is in particular the most productive firms that benefit from network effects in the form of rapid growth rates of their market shares (Van Alstyne et al., 2016; Zhu and Iansiti, 2019).

With respect to the development of the between-firm component over the three periods, we can observe a negative trend, which is a lot more pronounced for non-digital than for digital firms. While the contribution of digital firms shrank from 0.87% in the 1990-2000 period to 0.52% for 2008-2015, it decreased from 1.99% to only 0.16% for non-digital firms. When considering the contributions *per firm*, the sharp negative trend for non-digital firms is confirmed, while it is only slightly perceptible for digital firms. There does not seem to be a straightforward explanation for this clearly observable negative trend of non-digital firms. One possible reason may be that the above-mentioned lesser scalability of non-digital firms' business models is aggravated over time. Hence, while the already mature and most productive digital firms keep on increasing their market shares by exploiting their dominating position, the most productive non-digital firms might have reached a certain 'optimal' size which does not allow for further expansions without facing drawbacks in productivity. Another, somewhat related explanation may be the potential organizational inertia more frequently present in non-digital firms' business models (Boyer and Robert, 2006; Vorbach et al., 2017). Organizational inertia is considered as one of the most important factors preventing firms' value creation and change (Moradi et al., 2021). As Haag (2014) has argued, organizational inertia is known to be a barrier for accepting and adapting to technological evolutions such as, for instance, ICTs and digital technologies. Therefore, our findings could be explained by the resistance and inertia of a number of mature non-digital firms in adapting to technological change which directly affect their value-adding activities and, as a consequence, the development of their market shares.

**Productivity contribution of the cross-firm component**

We now turn to the second constituent part of the reallocation component, which is the cross-firm component, i.e., the dynamic reallocation component representing the interaction between changes in shares and changes in productivity. As shown in Table 2, it is consistently negative both for digital and non-digital firms. However, it is a lot more negative for non-digital than for digital firms, both the average contribution as well as the *per firm* contribution. While digital firms' cross component *per firm* varies between -0.0009% and -0.0020%, it is up to twice as negative for non-digital firms, varying between -0.0024% and -0.0030% (see Table 2). For non-digital firms, the negative cross-firm effect even exceeds the positive between-firm component which also explains our observation of an overall negative reallocation component shown in Figure 1.

The finding of a predominantly negative cross-firm effect is in line with what has been reported in previous studies on labor productivity growth (see e.g. Disney et al., 2003; Foster et al., 2001; Scarpetta et al., 2002). It implies a predominantly opposed development of market shares and productivity, which can manifest itself in two ways. First, it hints at a limited scalability of firms' business models: firms tend to increase their market share, that is, expand their business at the expense of their productivity. Second, it indicates a labor substitution effect: firms tend to increase productivity at the expense of their market share, that is, by reducing their labor force relative to competitors. These two potential causes are consistent with our above-mentioned observation of a more negative cross-firm effect for non-digital compared to digital firms. Concerning the first cause, we have already commented on the higher degree of business model scalability of digital firms in our statements regarding the between-firm effect. In addition to what we have stated above, note that digital firms' resource bundles allow them to allocate greater resources to multiple value-adding activities rather than exploiting them intensively in one specific activity. This facilitates digital firms' market share expansion and scalability not only within but also across business segments (Adner et al., 2019; Levinthal and Wu, 2010). Hence, the higher scalability makes it easier for digital firms to increase their market share without being exposed to significant losses of productivity. With respect to the second cause, that is, labor substitution effects, the more negative cross-firm component for non-digital firms implies that their productivity growth is more strongly driven by labor substitution than is the case for digital firms. A possible explanation for the less negative cross-firm effect of digital firms lies in the high labor investments needed to complement digital firms' exploitation of ICTs and digital technologies (Consolo et al., 2021; Jung et al., 2020; Spiezia, 2018). In fact, it has been argued that GPTs necessitate complementary investments in human capital to be fully operational, which could cause a less pronounced labor substitution effect for digital firms (Cette et al., 2021; Evangelista et al., 2014; Jung et al., 2020).

### 4.4 Productivity contribution of entering firms

With respect to the entry component, Figure 1 reveals a rather negligible contribution of entering firms to aggregate productivity growth. Recall that, in our dataset of publicly listed companies, 'entries' describe the events of newly listing company shares. As revealed in Table 2, the small aggregate impact of the entry component is caused by the small number of entering firms in our database, whereas the contribution *per firm* is, in fact, substantial. With the exception of digital firms in the 2001-2007 period, the contribution is consistently positive, implying that newly listed firms generally possess an above-average productivity upon entry. It is further worth noting that the firm-level contribution of non-digital entries substantially exceeds the firm-level contribution of digital ones, especially in the later two periods. However, the small number of entering firms sounds a notion of caution when drawing generalized conclusions regarding differences between digital and non-digital firms.

### 4.5 Productivity contribution of exiting firms

In analogy to the interpretation of entering firms, recall that 'exits' in our dataset are caused by delisting company shares. For exiting firms, Figure 1 shows a notable and mostly positive impact. This implies that it is generally the less productive firms that delist from the market. However, the impact is declining over time, in the last period it is even slightly negative for digital firms. What is particularly striking about the role of exiting firms is the very high average contribution *per firm* during the first two periods. With a maximum of as much as 0.0173% for digital and 0.0150% for non-digital firms, these contributions easily surpass the average contribution *per firm* reported for all other components (see Table 2).

This finding seems to be mainly caused by two factors. First, upon exiting the market, the overwhelming majority of exiting firms has a below-average productivity, with roughly 80% of exiting firms in the first period and 70% in the second period. Between 2008 and 2015, the share of exiting firms with below-average productivity is smaller but still exhibits a level of around 60%. This implies an efficiently working market mechanism that forces the less productive firms to delist their shares. Second, we observe several exits of very large firms with market shares of up to 13% within their three-digit industry and productivity levels significantly below the industry average. Since these are not matched by equally large exits with negative contributions, they effectuate a notable upward shift in the total and the *per firm* contribution. This imbalance in large exiting firms' contributions is particularly pronounced for digital firms, which helps to explain the more positive *per firm* contribution of exiting digital firms in the first two periods. During the 2008-2015 period, in contrast, this relationship is more balanced, which serves as a further explanation for the lower and, for digital firms, even negative contribution during that time. The reason for why we observe a delisting of such large firms seems to lie in the fact that a high share of delistings in our dataset is caused not by company closures but by M&A activities or firms becoming private. For example, the exit with the highest positive productivity impact in the 1990-2000 period was registered for Seagate Technology, which became a private company following a management buyout in 2000 (Seagate Technology LLC, 2000). Moreover, the largest exiting firm during the 2001-2007 period was Phelps Dodge which was acquired by Freeport-McMoRan in 2007 (Freeport-McMoRan, 2007). Hence, instead of entailing a shutdown of the respective exiting firms, these firms still exist either as part of a new parent company or in private ownership.

# 5 Conclusion

In this paper, we show substantial differences between digital and non-digital firms' contribution to productivity growth. Conducting a decomposition analysis on panel data of publicly listed U.S. manufacturing firms for the 1990-2015 period, we show that productivity growth in the manufacturing sector is mainly driven by firm-level efficiency improvements, with digital firms' contributions clearly dominating and exceeding those of non-digital firms. Moreover, we observe that the market selection process, i.e., the market's capability of channeling resources towards the most productive firms, works more efficiently for digital firms. Finally, our analysis shows that the negative correlation between productivity changes and changes in market shares is significantly less pronounced for digital than for non-digital firms. Drawing on the fact that digital firms are inherently distinct from non-digital firms with regard to their resource bundles, financial/cost structure, and competitive behaviour, we show how the observed differences in productivity growth can be linked to these idiosyncratic characteristics of digital firms. As the most essential aspects in this respect, we identify the higher degree in the exploitation of digital technologies, the greater scalability of digital business models which favors the creation of 'superstar' firms and the larger complementarity of digital and labor investments.

Like any study, this paper is subject to limitations, which offer potential avenues for future research. First, we rely on a fine-grained industrial classification to identify established players in digital industries. However, using such an industry classification and applying a specific threshold of digital intensity for identifying digital firms might also impose limitations, as it may not accurately capture all active digital firms. Future research could provide a complementary definition of digital firms, potentially by using different levels of digital intensity or by using a measure reflecting their exploitation of digital technologies based on patent data. A second limitation consists in the fact that our sample is composed of U.S. publicly listed firms from the manufacturing sector. Even though we substantiate our main conclusions on very universal differences of digital and non-digital business models, the generalizability of our findings to other datasets could be limited. It remains open to further research to analyze the extent to which our findings can be generalized to the private sector in the U.S., to other countries with different economic contexts as well as to sectors other than manufacturing. Third, on a similar note, our data is strongly fat-tailed and right-skewed. In line with the 'granular hypothesis' by Gabaix (2011), the aggregate developments we identify are significantly driven by a small number of very large firms, which especially applies to the group of digital firms. Hence, even though we emphasize how the emergence of these 'superstar' firms is an inherent characteristic of digital markets, it would certainly be insightful to conduct a decomposition exercise in less fat-tailed sectors to get a more direct, less skewed comparison of digital and non-digital firms' contribution to productivity growth.

In addition, future research should take into account the exploration of digital firms' exit by M&As and its impact on productivity growth. Considering the fact that M&As are intensively conducted to thrive in a more and more digitalized environment, it could be interesting to study the rate of digital firms' exiting an industry via acquisitions and compare it with non-digital firms' exit. Moreover, considering the current context, the COVID-19 shock seems to have further enhanced the use and adoption of digital technologies by non-digital firms. Future research could, for instance, evaluate how this acceleration in the pace of the digital transition alters the contribution of non-digital firms versus digital firms to productivity growth.

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# A NAICS three-digit manufacturing industries

Table 3: NAICS three-digit manufacturing industries 1990-2015

| | | Firm count | Sales | Employment | Productivity |
|---|---|---|---|---|---|
| 1990-2000 | | | | | |
| 331 | Primary Metals | 63.5 | 139,098.3 | 316.5 | 442.1 |
| 332 | Fabricated Metal Products | 92.3 | 98,439.0 | 339.8 | 291.2 |
| 333 | Machinery | 190.0 | 286,051.3 | 900.2 | 318.3 |
| 334 | Computer and Electronic Products | 480.5 | 179,561.9 | 1,463.9 | 122.1 |
| 335 | Electr. Equipm., Appliances, and Comp. | 70.3 | 69,768.6 | 311.5 | 225.2 |
| 336 | Transportation Equipment | 112.1 | 776,897.9 | 2,596.8 | 299.1 |
| 339 | Miscellaneous | 118.5 | 55,155.4 | 240.8 | 229.4 |
| 2001-2007 | | | | | |
| 331 | Primary Metals | 42.4 | 86,194.8 | 204.7 | 415.2 |
| 332 | Fabricated Metal Products | 62.1 | 80,001.4 | 337.3 | 236.1 |
| 333 | Machinery | 167.1 | 251,933.5 | 887.1 | 284.2 |
| 334 | Computer and Electronic Products | 502.9 | 423,115.1 | 1,852.7 | 229.4 |
| 335 | Electr. Equipm., Appliances, and Comp. | 67.9 | 62,474.7 | 283.2 | 220.0 |
| 336 | Transportation Equipment | 107.1 | 724,113.4 | 2,248.4 | 322.5 |
| 339 | Miscellaneous | 114.7 | 62,696.8 | 297.0 | 211.3 |
| 2008-2015 | | | | | |
| 332 | Fabricated Metal Products | 49.9 | 59,309.9 | 292.7 | 203.2 |
| 333 | Machinery | 123.6 | 205,294.2 | 1,005.6 | 205.9 |
| 334 | Computer and Electronic Products | 342.3 | 469,690.6 | 2,119.8 | 220.9 |
| 335 | Electr. Equipm., Appliances, and Comp. | 53.3 | 45,385.6 | 246.0 | 184.5 |
| 336 | Transportation Equipment | 84.3 | 647,847.4 | 1,792.6 | 361.6 |
| 339 | Miscellaneous | 88.3 | 52,048.4 | 259.7 | 200.3 |

*Notes*: The table shows the averages of annual three-digit industry-level values for firm count, sales, employment and productivity during the three periods considered in our study. All values are based on the cleaned sample as documented in Section 2. In accordance with this cleaning procedure, we excluded sector 331 (Primary Metals) in the 2008-2015 period, because the number of firms in the sample was below 30. Sales are reported in Million deflated US$, employment is in thousands, and productivity is measured as thousand deflated US$ per employee.

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