

Schiersch, Alexander; Stiel, Caroline

**Article**

## Testing the superstar firm hypothesis

Journal of Applied Economics

**Provided in Cooperation with:**

University of CEMA, Buenos Aires

*Suggested Citation:* Schiersch, Alexander; Stiel, Caroline (2022) : Testing the superstar firm hypothesis, Journal of Applied Economics, ISSN 1667-6726, Taylor & Francis, Abingdon, Vol. 25, Iss. 1, pp. 583-603,  
<https://doi.org/10.1080/15140326.2022.2029071>

This Version is available at:

<https://hdl.handle.net/10419/314176>

**Standard-Nutzungsbedingungen:**

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

**Terms of use:**

*Documents in EconStor may be saved and copied for your personal and scholarly purposes.*

*You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.*

*If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.*



<https://creativecommons.org/licenses/by/4.0/>



## Testing the superstar firm hypothesis

Caroline Stiel & Alexander Schiersch

**To cite this article:** Caroline Stiel & Alexander Schiersch (2022) Testing the superstar firm hypothesis, Journal of Applied Economics, 25:1, 583-603, DOI: [10.1080/15140326.2022.2029071](https://doi.org/10.1080/15140326.2022.2029071)

**To link to this article:** <https://doi.org/10.1080/15140326.2022.2029071>



© 2022 The Author(s). Published by Informa UK Limited, trading as Taylor & Francis Group.



Published online: 04 Apr 2022.



Submit your article to this journal [↗](#)



Article views: 3239



View related articles [↗](#)



View Crossmark data [↗](#)



Citing articles: 7 View citing articles [↗](#)

# Testing the superstar firm hypothesis

Alexander Schiersch and Caroline Stiel

Firms and Markets, Entrepreneurship Research Group, German Institute for Economic Research (DIW Berlin), Berlin, Germany

## ABSTRACT

Firms with superior productivity, labeled superstar firms, are argued to be the link between rising concentration and the fall of the aggregate labor share in the US. This analysis confirms that similar evidence is found within the European context: the market share and firm size increase, whereas the labor share decreases with productivity. One of the much discussed mechanisms behind this development is the spreading of fixed overhead labor costs: Highly productive firms gain market share, and can simultaneously spread fixed overhead labor costs over more output, thereby reducing their own labor share and the aggregated labor share of the industry. We show that this mechanism can be tested empirically. However, using German firm-level data, we do not find any empirical evidence of it. Our analysis contributes to the ongoing debate by removing one of the proposed mechanisms from the list of potential explanations for the rise of superstar firms.

## ARTICLE HISTORY

Received 26 March 2021

Accepted 30 December 2021



## KEYWORDS

Superstar firms; total factor productivity; labor share; firm size

## 1. Introduction

An increasing number of studies suggest a rise of market power of firms and a growing concentration within many economic sectors (De Loecker, Eeckhout, & Unger, 2020; Grullon, Larkin, & Michaely, 2019; Rossi-Hansberg, Sarte, & Trachter, 2021; Van Reenen, 2018).<sup>1</sup> Simultaneously, the literature discusses the potential reasons for the shrinking share of labor in GDP and rising inequality in most advanced economies (Bourguignon, 2017; Elsby, Hobijn, & Sahin, 2013; Karabarbounis & Neiman, 2014; Mertens, 2019; Nolan, Richiardi, & Valenzuela, 2019; Rodriguez & Jayadev, 2013).

Autor, Dorn, Katz, Patterson, and Van Reenen (2017a,b, 2020) developed the widely recognized superstar model that links both observations and provides a possible explanation for them. The model predicts that superstar firms, i.e., firms with superior productivity, have higher sales and, thus, capture a larger share of the market, leading to growing concentration in the economy. If superstar firms have below-average labor shares, they could be the channel linking the growing concentration with the falling labor share that is observed at the industry level. The hypothesis that the decline in the aggregate labor share is driven by highly productive firms with below-average labor shares gaining market

**CONTACT** Caroline Stiel  [cstiel@diw.de](mailto:cstiel@diw.de)  German Institute for Economic Research (DIW Berlin), Mohrenstr. 58, 10117 Berlin, Germany

<sup>1</sup>Whether increasing concentration, growing markups, and a reduction of competition intensity is a general phenomenon of advanced economies is still debated (Gutiérrez & Philippon, 2018; Traina, 2018).

© 2022 The Author(s). Published by Informa UK Limited, trading as Taylor & Francis Group.

This is an Open Access article distributed under the terms of the Creative Commons Attribution License (<http://creativecommons.org/licenses/by/4.0/>), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

shares is not new and is studied elsewhere (e.g., Böckerman & Maliranta, 2012; Hartman-Glaser, Lustig, & Xiaolan, 2019; Kehrig & Vincent, 2021). Autor et al. (2017a,b, 2020) provide two explanations for *why* superstar firms would have below-average labor shares: (i) above average firm-level markups; and (ii) fixed overhead labor costs. The first view is based on a model of monopolistic competition, where labor shares are decreasing as markups increase. The second explanation addresses “fixed costs of overhead labor” (Autor, Dorn, Katz, Patterson, & Reenen, 2020, p.654). Because of their size, Autor et al. argue that superstar firms are able to spread fixed overhead costs, especially fixed labor costs, over more output, thus having lower labor shares. It is important to notice that the two mechanisms are not mutually exclusive and could both drive down the labor share.

However, the two mechanisms proposed by Autor et al. have contrary implications for economic policy, notably for antitrust. As we discuss more extensively in the paper, there are concerns in antitrust that highly productive firms exploit their market position to charge excessive prices and engage in anti-competitive practices to shut competitors out of the market. If the lower labor share of highly productive firms is a result of market power that translates into high markups, the rise of superstar firms would be problematic from a competition point of view. If instead superstar firms are just more efficient, the growing concentration has to be seen as a result of a fierce(r) competition and the below-average labor shares would simply reflect higher cost efficiency. Because of these far-reaching and contrary implications, it is important to uncover the channels through which the firms’ labor shares are affected. Autor et al. (2020) provide evidence for the markup mechanism but not for the fixed-costs mechanism. To the best of our knowledge, the fixed-costs mechanism proposed in the superstar model is not yet tested empirically and its relevance in explaining labor share changes is not yet assessed. This paper aims to fill this gap.

First, we test whether the general link between firm size, total factor productivity (TFP), and the labor share can be confirmed within the European context. Broadening the US analysis with international evidence, Autor et al. (2020) claim that the superstar models holds across a large range of OECD countries, including Germany. However, they focus on the macro-level, i.e., on the link between industry concentration and the labor share, as well as the reallocation of market shares. They do not analyze firm-level productivity outside of the US. Using German firm-level data, we analyze whether (i) the larger the TFP of firms, the larger they are and the higher their market shares; and (ii) the larger the TFP of firms, the lower their labor shares. Thereafter, we address the mechanism underlying this phenomenon and explicitly test the fixed-costs mechanism proposed in Autor et al. (2017a,b). We argue that the theoretically described mechanism has a testable implication and demonstrate that it imposes a non-linear relationship between the firms’ TFP and their labor shares, with weaker marginal effects for high productive firms if the mechanism is correct. We then empirically test whether we find support for such a relationship.

Across a large number of different sectors of the German business economy, we indeed find that the firms’ labor share decreases with their TFP, while the market share increases with TFP. Consequently, we find that superstar firms, as measured by the top 10% of the TFP distribution, have the highest value added and the lowest labor shares. However, our analysis finds no evidence for the underlying fixed-costs mechanism. Thus, our analysis contributes to the ongoing debate by deleting one of the proposed

mechanisms from the list of potential explanations for the rise of superstar firms and the cause of falling labor shares. It also strengthens the interpretation that the rise of superstar firms poses a threat to competition, because the alternative mechanism, that is, growing market power and rising markups, seems to be more relevant.

The remainder of the paper is organized as follows. [Section 2](#) describes the superstar model and develops the propositions. [Section 3](#) briefly presents the ongoing debate and different views on the rise of superstar firms and their impingement for competition. [Section 4](#) presents the data and outlines the empirical approach to test the propositions. [Section 5](#) presents the results and discusses their implications for the debate on superstar firms and competition policy. The last section concludes.

## 2. The superstar model

### 2.1. Propositions of the superstar model

The superstar model in Autor et al. (2020) focuses on the role of firm-level markups and is a reduced version of the more general model presented in Autor et al. (2017a,b), which allows for the existence of both fixed overhead labor costs and firm-level markups.<sup>2</sup> Notably, Autor et al. (2017a,b) assume that total labor ( $L_i$ ) is the sum of a fixed amount of overhead labor ( $F$ ), equal to each firm, and of a firm-specific amount of variable labor that is required in production ( $V_i$ ).

Both models use a standard Cobb-Douglas production function with constant or decreasing returns to scale. Labor elasticity ( $\alpha_L$ ) is identical across firms, as factor markets are assumed to be competitive, such that neither wages ( $w$ ) nor capital costs ( $r$ ) are firm specific. Furthermore, firms differ with respect to their total factor productivity ( $\Omega_i$ ) and firms with higher productivity “will have higher levels of factor inputs and greater output” (Autor et al., 2020, p.653). In other words, firm size increases with TFP. This also leads to the proposition that the higher the productivity of a firm relative to its peers in the industry, the larger is its market share. This important nexus is theoretically established by Autor et al. (2017a) but only empirically tested with firm-level US data in Autor et al. (2020). Whether this property also holds within the European context is the first hypothesis to be tested.

**Proposition 1:** The larger a firm’s TFP, the larger is the firm’s output and the larger is its share of the market.

Labor share is defined as  $S_i = wL_i/(PY)_i$ , with nominal value added as the denominator. In Autor et al. (2017a,b), this is identical to  $S_i = wV_i/(PY)_i + wF/(PY)_i$ , with  $F$  denoting fixed overhead labor and  $V$  the remaining labor. The latter is supposed to be variable in the sense that its level changes with the output of firms. Due to model assumptions, the first ratio is

---

<sup>2</sup>For a detailed presentation of both models, we refer to [Appendix A](#) in Autor, Dorn, Katz, Patterson, and Van Reenen (2017b) and [Appendix A](#) in Autor et al. (2020).

constant across all firms and identical to the labor elasticity ( $\alpha_L$ ). If firms are able to exploit market power, markups  $\mu_i$  (price to marginal cost ratio) are different from 1 and the labor share can also be written as (Autor et al., 2017a, p.181):

$$S_i = \frac{\alpha_L}{\mu_i} + \frac{wF}{(PY)_i}. \quad (1)$$

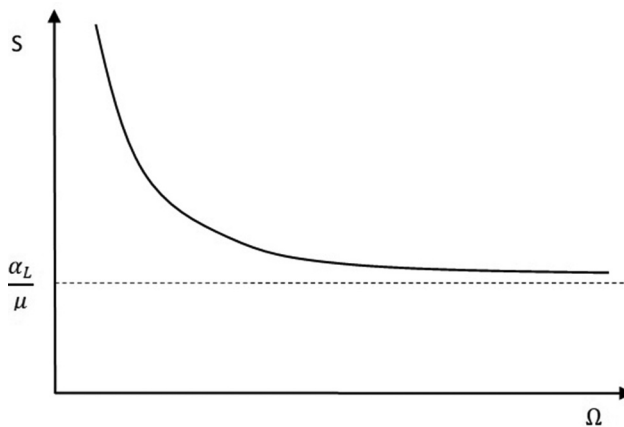
From equation (1), we see that a decrease in the firm-level labor share can stem from two sources: an increase in the markup, as argued in Autor et al. (2020), and the spread of fixed overhead labor costs over more output, as argued in Autor et al. (2017a,b). These two mechanisms do not mutually exclude each other and can be simultaneously at work. To study the impact of the second component, fixed overhead labor costs, we make a simplifying assumption and follow Autor et al. (2017a,b) in assuming that  $\mu_i = \mu$  within an industry. Consequently, the first term in equation (1) is constant across all firms. In contrast, the value of the second component, the ratio of fixed overhead labor over value added, is decreasing in value added. Because value added increases with TFP, the model implicitly presumes a negative relationship between TFP and the labor share of firms. This leads to the second proposition to be tested in this study.

**Proposition 2:** The larger a firm's TFP, the lower its labor share.

## 2.2. The fixed-costs mechanism of the superstar model

While the previous section focuses on testing the two main properties assumed for superstar firms, this section describes the underlying fixed-costs mechanism and shows its testable implication.<sup>3</sup>

Although not discussed by Autor et al. (2017a,b), equation (1) implies what the relationship between labor shares and TFP in general must look like. As depicted in Figure 1, it must be a non-linear relationship with negative marginal effects that are decreasing in magnitude as TFP increases. In fact, the marginal effect must converge



**Figure 1.** Relationship between the labor share and TFP in the superstar model.

toward zero as the labor share converges toward  $\alpha_L/\mu$  as we move along the TFP distribution. Put differently, the labor share should fall more steeply at the lower tail of the TFP distribution, since the fixed overhead labor is spread over a small output and the marginal effect of an additional unit of output is large. In contrast, the premium on  $\alpha_L/\mu$  due to  $wF/(PY)_i$  is already minimal for the large superstar firms, and the marginal effect of an additional unit of  $(PY)_i$  will be minimal. Even without knowing the precise shape of the curve, this insight allows for testing whether the assumed mechanism is empirically supported.

**Proposition 3:** The relationship between TFP and labor share is non-linear, where the marginal effects at the left tail of the TFP distribution must be larger than at the right tail of the TFP distribution.

### 3. Implications for antitrust

Besides providing a compelling theoretical explanation for the growing concentration in most industries and the simultaneously observed fall in labor shares, the superstar model has some important implications for economic policy, notably for antitrust enforcement. The central question is whether the rise of superstar firms is desirable from a competition point of view or should be seen with caution. Proposition 1 describes the result from a selection process where low-productive firms have little or even lose market shares while a growing part of the market is occupied by high-productive firms. If the theoretical proposition can be confirmed empirically, this would be a sign that the markets work efficiently. In addition, the fixed-costs mechanism underlying Proposition 2 suggests that highly productive firms are more labor-efficient and one reading of the growing concentration could be that it is a result of fierce competition where superstar firms benefit from cost advantages. In conclusion, the simultaneous occurrence of growing concentration and falling labor shares *a priori* would not be an indication of market failure.

On the other hand, the markup mechanism that is proposed as an explanation for Proposition 2 within the superstar model suggests that the falling labor share in highly productive firms reflects their ability to increasingly charge above marginal costs. Hence, one might be concerned that highly productive firms do not just gain market share but also market power, and that they subsequently exploit their dominance to charge excessive prices or to engage in anti-competitive practices like exclusive dealing clauses, requirements contracts, or product tying. Thus, identifying the causes for the below-average labor shares in highly productive firms helps to understand the firms' rise and their role in the competitive environment. The following section summarizes previous evidence on abusive behavior that is supposedly linked to the rise of superstar firms.

---

<sup>3</sup>If information on fixed overhead labor costs would be available in the data, it would be straightforward to test the fixed-costs mechanism by contrasting the fixed overhead labor costs shares against the TFP distribution. Unfortunately, we do not have such detailed data, which is why we choose an alternative way for testing the mechanism.

### 3.1. Market power and excessive prices

Whether market power and markups are growing is an ongoing debate in the empirical literature. De Loecker et al. (2020) find a substantial increase in markups in the US from 21% above marginal costs in 1980 to 61% in 2016 and show that the increase is mostly driven by increasing markups of highly productive firms, whereas the median markup stayed constant. Furthermore, they argue that the increase in markups cannot be explained by rising overhead costs, but indeed reflects greater profitability and excessive prices. Thereby, it distorts the distribution of economic rents and impedes consumer well-being, providing potential reasons for increased vigilance by antitrust authorities. The study of De Loecker et al. (2020) is one of the latest in a series of studies that diagnose increasing market power, declining competition, and increasing markups; *inter alia*, Rossi-Hansberg et al. (2021); Grullon et al. (2019); Van Reenen (2018).

The occurrence of an increase in markups, however, is debated. Karabarbounis and Neiman (2019), Traina (2018), and Karabarbounis and Neiman (2014) argue that the increasing wedge between costs of goods sold and sales cannot easily be identified as markup, but could also stem from technological change implying rising overhead costs, unmeasured capital, increasing substitution of labor with capital, and difficulties in correctly measuring the rental rate of capital. Related to this, Bond, Hashemi, Kaplan, and Zoch (2020) Gandhi, Navarro, and Rivers (2020) and Flynn, Gandhi, and Traina (2019) present reasoned criticism regarding the methodology behind the markup estimation used in Autor et al. (2020) and De Loecker et al. (2020), discussing a wide range of problems involved in firm-level markup estimation.<sup>4</sup>

### 3.2. Abuse of dominant market position

The rise of superstar firms is characterized by the growing concentration in many markets. However, there is no general perception of how large is too large. Ultimately, whether a firm's market share has become so large that it indicates a dominant position must be considered case by case and also depends on the specific national antitrust laws. Yet, while this prevents a general statement about whether or not superstar firms pose a threat to competition due to their pure size, analyzing recent antitrust cases provides useful insights in the challenges to competition by very large firms, lately particularly in the digital markets.

While there have been relatively few decisions against firms at the national level,<sup>5</sup> the number of investigations led by the European Commission into US Tech companies like Google, Facebook, Microsoft, and Amazon – which most people would probably label as “superstar firms” – has substantially increased. The issues at stake are anti-competitive contractual restrictions such as requirements contracts (Google AdSense – Case, 2019; Intel – Case, 2009; Qualcomm – Case, 2018), most-favored-nation clauses (Amazon – Case, 2017), illegal product tying (Google Android – Case, 2019; Microsoft – Case, 2007),

---

<sup>4</sup>Notably, Bond et al. (2020) argue that the ratio between output elasticity and cost shares does not contain any meaningful information on markups if the production function is estimated with revenue data. Furthermore, problems arise if inputs are used to influence demand (e.g., marketing expenditure), or if firms have market power and markups are heterogeneous. Gandhi et al. (2020) and Flynn et al. (2019) discuss cases where the nonparametric estimation routine of the control function approach is underidentified.



and giving advantage to own subsidiaries on platforms (Google Shopping – Case, 2018). While abuse of a dominant market position exists in other industries as well and is not a new phenomenon in antitrust enforcement, there is a rising concern that data-driven markets are characterized by high entry barriers resulting from economies of scale and scope as well as that highly productive firms in digital markets quickly become quasi-monopolists, e.g., through platform business models with strong network effects (Prüfer & Schottmüller, 2017; Rubinfeld & Gal, 2017; Stucke & Grunes, 2015). Thus, a challenge in antitrust policy is to take the (partially) novel characteristics of digital markets into account and to adapt the antitrust authorities' competencies and their investigation criteria accordingly (Argentesi et al., 2019). For example, the 2017 reform of the German competition law updated the notion “relevant market” to include markets without monetary flows between producers and consumers, as is the case with many internet-based offers such as search engines or comparison portals (GWB §18(2a)); and explicitly extends the investigation criteria to the role of network effects, the behavior of user groups, and the access to competition-relevant data (GWB §18(3a)). Potential antitrust measures against superstar firms in data-driven markets that are currently discussed include obligations to share data with competitors and unbundling requirements (see the Facebook – Case (2019) by the German *Bundeskartellamt* and Detrixhe (2019), Stuehmeier (2018)). Furthermore, to assess the role of data collection for competition, the European Commission recently opened three more investigations into Amazon (Amazon Marketplace – Case, 2019), Facebook, and Google (Amaro, 2019).

These different cases and rulings show that the dominant position of very large firms and their ability to exploit market power as well as their actual behavior, is increasingly seen as an issue by antitrust authorities.

#### 4. Data and empirical approach

The analysis uses the IAB Establishment Panel (IAB-EP), an annual survey of about 16,000 establishments covering the entire German economy. The survey is conducted by the Federal Employment Agency and representative at industry-group and federal state levels (Fischer, Janik, Müller, & Schmucker, 2009).<sup>6</sup> Our dataset covers the 1996 to 2016 period. During the data preparation process, we drop observations with missing values in one of the basic variables, e.g., labor, value added, etc., and perform an outliers detection. The final dataset contains 132,134 observations. We follow Autor et al. and the standard literature in deflating all monetary values using deflator time series provided by the Federal Statistical Office at the two-digit NACE industry level. We provide the descriptive statistics of the variables in Table 1.

As in Autor et al. (2020), we use a standard Cobb-Douglas production function with two inputs, labor  $L_{it}$  and capital  $K_{it}$ , with which firm  $i$  in year  $t$  produces the output  $Y_{it}$  that is measured by value added. The production function is then given by

<sup>5</sup>Between 1999 and 2019, the German Federal Cartel Office convicted 65 firms of abusing their dominant position. However, the vast majority of these cases are related to the liberalization of energy markets and were filed against utilities. Since 2010, only three decisions concerned companies outside of network infrastructure industries: one pharmaceutical company (Merck in 2011), a ticket seller (CTS Eventim in 2017), and the US tech firm Facebook (2019).

<sup>6</sup>We provide a detailed description of the data source and how it can be accessed in [Appendix A](#).

**Table 1.** Descriptive statistics.

Variable	Description (unit)	P5	Mean	Median	P95	Std. Dev.	N
$P_{it}Y_{it}$	value added (mio EUR)	0.04	12.0	0.72	36.1	132.6	132,134
$K_{it}$	capital (mio EUR)	0.06	30.4	0.99	78.9	284.2	132,134
$M_{it}$	material (mio EUR)	0.02	22.1	0.58	49.8	411.8	132,134
$wL_{it}$	wagebill (mio EUR)	0.01	4.7	0.37	15.0	46.6	132,134
$L_{it}$	employees	2	129	18	461	909	132,134
$S_{it}$	labor share	0.12	0.59	0.49	1.40	0.48	132,134

Source: IAB Establishment Panel, 1993–2017, own calculations. DOI: 10.5164/IAB.IABBP9317.de.en.v1

$$y_{it} = \beta_l l_{it} + \beta_k k_{it} + \omega_{it} + \epsilon_{it} \quad (2)$$

where  $\epsilon_{it}$  is a measurement error assumed to be iid and lower case letters denote logs. The firms' TFP ( $\Omega_{it}$ ) are estimated by means of the control function approach of Akerberg, Caves, and Frazer (2015). The control function approach is widely used for estimating firm-level TFP, since it offers a solution for tackling the simultaneity bias arising from endogenous productivity in the production function (see, e.g., Aw, Roberts, & Xu, 2011; Collard-Wexler & De Loecker, 2015; De Loecker et al., 2020; Doraszelski & Jaumandreu, 2013; Parrotta, Pozzoli, & Pytlikova, 2014). It has also been applied to German data in many different contexts (e.g., Peters, Roberts, Vuong, & Fryges, 2017; Richter & Schiersch, 2017; Stiel, Cullmann, & Nieswand, 2018). All analyses, including the TFP estimation, are carried out at the industry level, following the official NACE aggregation scheme A\*38 by the European Commission (EC, 2010).

Autor et al. (2017a,b, 2020) do not explicitly define superstar firms. In our analysis, we follow the literature and define these firms as belonging to the top decile of the TFP distribution within each industry (see, among others, Andrews, Criscuolo, & Gal, 2019, 2016, 2015; Bartelsman & Zoltan, 2017).<sup>7</sup> We test Proposition 1 by analyzing the distribution of firm size per TFP deciles and by means of a bivariate regression of market shares on TFP. The regression equation is given by

$$ms_{it} = \frac{P_{it}Y_{it}}{\sum_i P_{it}Y_{it}} = \beta_0 + \beta_1 \omega_{it} + \tau_t + \eta_s + \epsilon_{it}, \quad (3)$$

where  $ms_{it}$  is the firm's market share in the industry,  $\omega_{it}$  is the logged TFP at time  $t$  of firm  $i$ ,  $\tau_t$  are time dummies,  $\eta_s$  are sector fixed effects at the NACE 2-digit level, and  $\epsilon_{it}$  is the error term. The errors are clustered at the firm-level and bootstrapped with 1,999 replications.

Proposition 2 is tested using the subsequent equation:

$$S_{it} = \frac{wL_{it}}{P_{it}Y_{it}} = \gamma_0 + \gamma_1 \omega_{it} + \tau_t + \eta_s + u_{it}. \quad (4)$$

The assumed non-linear relationship between TFP and the labor share, as depicted in Figure 1, is best described by a polynomial of order 2. Therefore, equation (4) is extended by the term  $\gamma_2 \omega_{it}^2$  when empirically verifying Proposition 3. The marginal effect of TFP on the labor share then depends on the TFP distribution and is given by

<sup>7</sup>We also tested the 5%-threshold for separating the top productive firms. Due to data privacy restrictions, we can only publish the results for the top decile. However, the results, e.g., Figure 2, do not change qualitatively when using the 5% threshold.

$$\theta_{it} = \gamma_1 + 2\gamma_2\omega_{it}. \quad (5)$$

In both estimations we cluster the errors at the firm-level and bootstrap them with 1,999 replications.

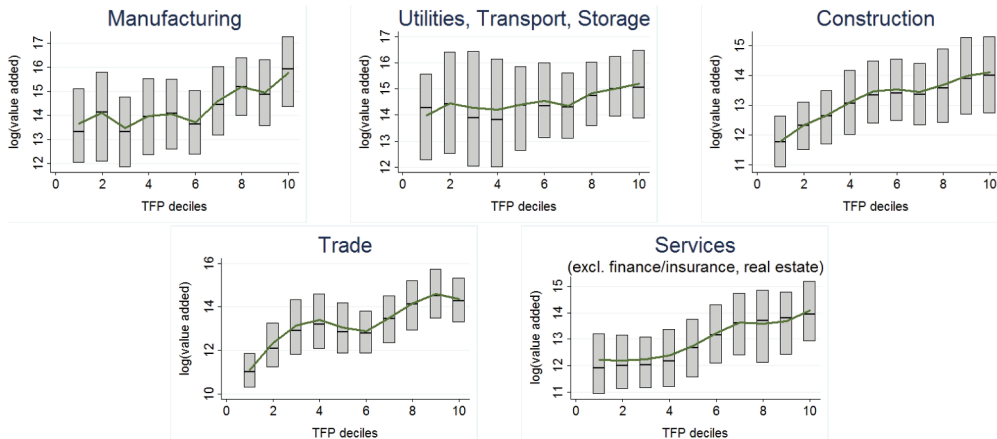
## 5. Results

### 5.1. Concentration, market share, and productivity

We start by analyzing whether the phenomenon of a negative correlation between the aggregate labor shares and industry concentration, which the superstar model aims to explain, is also observable in our data. This is a necessary prerequisite for the subsequent analyses. Standard concentration measures are the Herfindahl-Hirschman Index (HHI) and the Concentration Ratio (CR). We closely follow Autor et al. by applying the latter and use the CR20 measure containing the aggregate market share of the top 20 firms.

Indeed, Table 2 shows that industry concentration is negatively correlated with the aggregate labor share in that industry.<sup>8</sup> The results hold both in levels and the 5-year-differences specification that are also employed by Autor et al. (2017a,b, 2020).

Figure 2 addresses the first part of Proposition 1, presenting the relationship between firm size and TFP at the aggregate industry level. We partition the sample into deciles using the TFP distribution. The bars show the interquartile range of firm size within each TFP decile. The dash in each bar indicates the median. The solid lines depict the means.



**Figure 2.** Value added by deciles of the TFP distribution. Note: The bars are defined by the interquartile range of value added. Each bar includes a dash that marks the median. The solid lines depict the means. TFP estimated by means of the ACF approach. Source: IAB Establishment Panel, 1993–2017, own calculations. DOI: 10.5164/IAB.IABBP9317.de.en.v1

We find that the superstar firms, i.e., the firms in the top decile of the TFP distribution,

<sup>8</sup>Besides the CR20-indicator, Autor et al. (2017a) also employ the CR4-indicator. The data privacy restrictions of the IAB do not allow us to present the results for the CR4- or even the CR10-indicator. However, the results we were able to visually inspect via remote access confirm that the relationship remains negative and significant for these concentration rates.

**Table 2.** Regression of (changes in) labor shares on (changes in) concentration.

	CR20		Constant		R <sup>2</sup>	N
Levels	– 0.555 ***	(0.123)	0.664 ***	(0.092)	0.66	567
Logs	– 0.818 **	(0.230)	– 1.664 ***	(0.069)	0.57	567
5-year-change	– 0.672 ***	(0.097)	0.026 ***	(0.000)	0.32	432

Notes: \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ . Parentheses contain standard errors. Standard errors are clustered at industry-level and are robust to serial correlation and heteroscedasticity. All calculations include year dummies and dummies for industries. Dependent variable in the OLS is the labor share. Source: IAB Establishment Panel, 1993–2017, own calculations. DOI: 10.5164/IAB.IABBP9317.de.en.v1

are mostly the largest in terms of value added. The only exception is the trade sector, where value added is slightly larger in the second highest decile. The charts also reveal that not only do the mean and median of firm size increase along the TFP distribution, but also the entire distribution of firm size shifts upwards. This general pattern also holds for a more refined industry level.<sup>9</sup> This supports the assumption of Autor et al. (2017a,b, 2020) regarding the nexus between firm size and TFP.

We test the second part of Proposition 1, by means of a regression analysis. Column (1) of Table 3 contains the marginal effects of a change in total factor productivity on the market share.<sup>10</sup> The coefficients are positive and significant in 15 of the 21 industries, showing that market share indeed increases with TFP. In cases where the results are negative, they are insignificant with one exception. Taking the example of the food industry, the market share increases an average of 0.01 percentage points when the TFP increases by one percent. All-in-all, the two analyses confirm the first Proposition: the more productive the firms, the bigger they are and the larger their market share.

The results in column (2) of Table 3 address Proposition 2. The presumed negative link between TFP and the labor share is confirmed for nearly all industries. However, the effect seems to be less pronounced in service industries, including even positively significant coefficients in tourism and professional activities. An explanation for the weaker link between TFP and the labor share might be that service industries are usually more (variable) labor-intensive, such that the relative savings on labor costs from fixed overhead labor might be less important as the firm size increases. In the other sectors, the labor share reacts quite strongly to changes in TFP. Taking again the example of the food industry, the labor share of a firm is 0.24 percentage points smaller if the TFP increases by one percent.

## 5.2. The fixed-costs mechanism

As outlined in Section 2.2, the fixed-costs mechanism of the superstar model requires that the negative marginal effect of TFP on the labor share is stronger at the lower tail of the TFP distribution and should continuously decrease in magnitude as we move toward the upper tail of the TFP distribution. This requires the estimation of a second order polynomial. The respective results are shown in Columns (3) to (5) of Table 3. They contain the marginal effects at the tenth, the fiftieth, and the ninetieth quantiles of the TFP distribution.

<sup>9</sup>See Figure C1 in the Appendix C for a more detailed analysis.

<sup>10</sup>We exclude the sectors of vehicle manufacturing and finance/insurance from the analysis, due to implausible coefficients for labor or capital obtained in the production function estimation. The respective coefficients are shown in Table B1 in the Appendix B.

**Table 3.** Regressions of market shares and labor shares on TFP.

	Market shares		Labor shares				
			Nonlinear effects				
	Linear		Linear		p10	p50	p90
Industry	(1)		(2)		(3)	(4)	(5)
<b>Manufacturing</b>							
Food/beverages	0.010***	(0.002)	−0.243***	(0.032)	−0.147	−0.199	−0.282
Textiles	0.013***	(0.003)	−0.246***	(0.033)	−0.306	−0.262	−0.201
Wood/paper	0.006***	(0.001)	−0.039	(0.050)	0.054	−0.042	−0.125
Chemicals/pharma.	0.017*	(0.008)	−0.193***	(0.038)	−0.172	−0.188	−0.208
Rubber/plastics	−0.004***	(0.001)	−0.126***	(0.033)	−0.083	−0.113	−0.146
Metal	0.002*	(0.001)	0.024	(0.040)	0.236 +	0.082 +	−0.080 +
Electronics /electric eq.	0.007***	(0.002)	−0.111*	(0.046)	−0.130	−0.111	−0.092
Mechanical engineering	0.008***	(0.001)	−0.100**	(0.037)	−0.065	−0.105	−0.134
Others and repairing	−0.001	(0.002)	−0.138**	(0.051)	−0.062	−0.119	−0.184
<b>Utilities</b>	−0.004	(0.002)	−0.162***	(0.031)	−0.122	−0.152	−0.189
<b>Construction</b>	0.003***	(0.001)	−0.074**	(0.026)	0.060 +	−0.026 +	−0.121 +
<b>Trade</b>							
Trade of motor vehicles	0.008***	(0.002)	−0.118***	(0.031)	−0.105	−0.116	−0.127
Wholesale trade	0.003**	(0.001)	−0.049*	(0.022)	0.066 +	−0.036 +	−0.129 +
Retail trade	0.001**	(0.000)	−0.119***	(0.018)	−0.078	−0.112	−0.141
<b>Transport &amp; storage</b>							
Transportation	0.006**	(0.002)	−0.126*	(0.053)	−0.049	−0.117	−0.188
Storage/postal services	0.005*	(0.002)	−0.109**	(0.036)	−0.025	−0.086	−0.166
<b>Services</b>							
Tourism	0.014***	(0.003)	0.114*	(0.047)	0.151	0.119	0.080
Information/commu.	−0.010	(0.010)	0.042	(0.048)	0.027	0.047	0.060
Real estate	−0.004	(0.003)	−0.117***	(0.030)	−0.197	−0.105	−0.050
Professional activities	−0.002	(0.002)	0.154***	(0.038)	0.054	0.149	0.249
Support services	0.008**	(0.003)	−0.086***	(0.021)	−0.057	−0.080	−0.108

Notes: \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.001$ . OLS estimations with block-bootstrapped standard errors in parentheses. TFP estimated by means of the ACF approach with detailed results given in Table B1 in the Appendix B. Coefficients for the market shares are obtained from estimating equation (3). The marginal effects for the labor shares in columns (3) to (5) are obtained from estimating equation (4) and computing the marginal effect for the p10, p50, and p90 quantiles of the TFP distribution using equation (5). The coefficients  $\hat{\gamma}_1$  and  $\hat{\gamma}_2$  from equation (4) are not significant at  $p < 0.05$  unless specified with "+". Detailed regression results for equation (4) are given in Table B2 in the Appendix B. The financial industry is excluded because of its insignificant capital coefficient and motor vehicle manufacturer because of its implausible labor coefficient of more than one. Source: IAB Establishment Panel, 1993–2017, own calculations. DOI: 10.5164/IAB.IABBP9317.de.en.v1

The nonlinear specification's first and second-order coefficients are significantly different from zero only in 3 out of 23 industries, marked by "+" in the table.<sup>11</sup> Furthermore, the marginal effects in these industries point to a positive link between the labor share and the TFP at the left tail of the productivity distribution, and a negative effect at the right tail of the TFP distribution, i.e., for superstar firms. Both the insignificance in most industries and the opposite trend of the marginal effects across the TFP distribution contradict the mechanism that stresses the role of fixed overhead labor costs. If the mechanism held, small, low-productive firms would incur relatively higher cost savings from expanding firm size than superstar firms and we should find a strongly negative marginal effect at the 10-percent TFP-quantile that gradually *increases* toward zero. Hence, Proposition 3 is rejected by the empirical results. Thus, our results speaks

<sup>11</sup>Detailed regression results are provided in Table B2 in the Appendix B.

against the fixed-costs mechanism as proposed in Autor et al. (2017a,b). Fixed overhead labor costs do not seem to be the main explanation for the superstar firms' low labor shares.

### 5.3. Robustness checks

Wanting to stay as close as possible to the model of Autor et al. (2017a,b) when testing the fixed-costs mechanism, we followed the authors in assuming  $\mu_i \equiv \mu$  within each industry (see Section 2.1). However, this assumption might be overly restrictive as firm-level markups could vary between firms of the same industry. In fact, variation in market power is at the core of the alternative explanation proposed in Autor et al. (2020). If markups vary between firms, firm-level TFP estimates  $\tilde{\omega}_{it}$  would be biased as can be seen from equations (6) and (7) where  $y_{it}$  denotes logged value added adjusted for the 2-digit industry price index and  $\omega_{it}$  is the true TFP.

$$Q_{it} = \frac{VA_{it}}{P_{it}\mu_{it}} = L_{it}^{\beta_l} K_{it}^{\beta_k} \Omega_{it} \exp \epsilon_{it} \quad (6)$$

$$y_{it} = \beta_l l_{it} + \beta_k k_{it} + (\underbrace{\omega_{it}}_{\tilde{\omega}_{it}} + \ln(\mu_{it})) + \epsilon_{it}, \quad (7)$$

Therefore, as a robustness check, we apply the approach suggested by Andrews et al. (2016) and compute  $\omega_{it} = \tilde{\omega}_{it} - \ln \mu_{it}$ . Firm-level markups are estimated following De Loecker and Warzynski (2012). Table B3 in the Appendix shows that the main findings remain unchanged, i.e., the fixed-costs mechanism is rejected and market shares and TFP are positively correlated.

Furthermore, we tested whether these results are sensitive to the approach chosen for estimating the TFPs by calculating the underlying output elasticities for firm-level TFP with industry-specific cost shares, which has been used, among others, in Foster, Haltiwanger, and Syverson (2008) and De Loecker et al. (2020). The respective results are in line with the above results. Hence, we find a negative correlation between the markup-corrected TFP and the labor share, but no evidence for a convex pattern.<sup>12</sup>

### 5.4. Discussion

The results show that the most productive firms are usually the largest in terms of value added, having the largest share of the market, and that this is observed across a wide range of industries. This does not just hold for the top decile, but the market share steadily increases with TFP, confirming a selection process where low-productive firms lose market shares or do not gain significant market shares after entry. From an efficiency point of view, this points to a sound competitive environment in which highly productive firms prevail, thereby increasing aggregate industry efficiency. However, note that our findings are limited by the fact that the economic classification is broad and we can neither zoom into specific markets, nor can we assess whether the aggregate efficiency level is close to the technological frontier.

<sup>12</sup>Detailed regression results are available upon request from the authors.

Whereas Propositions 1 and 2 are confirmed, the fixed-costs mechanism is rejected, suggesting that highly productive firms do not enjoy significant cost advantages from distributing fixed overhead labor costs over more output. This shifts the focus toward other mechanisms discussed in the literature, notably the role of markups brought up in Autor et al. (2020). As becomes clear from the first term in equation (1), an increase in markups can also explain the decrease in firm-level market shares, with stronger effects for firms with above-average markups. If highly productive firms exploit their market position to charge higher markups than others, we would equally obtain the negative correlation between TFP and firm-level labor shares shown in Table 3, Column (2). In line with this, De Loecker et al. (2020) argue that the observed increase in markups in the US cannot be justified by higher overhead costs but rather reflects increasing market power, that is, excessive pricing. In conclusion, the empirical evidence established in this paper suggests that the below-average labor shares in highly productive firms do not simply reflect cost efficiency but indeed could be a sign of market power. Therefore, future research should study more closely the market power of superstar firms and potential implications for antitrust enforcement.

## 6. Conclusion

Autor et al. (2017a,b, 2020) developed the superstar model that provides a compelling explanation for two simultaneously occurring phenomena: the shrinking of labor shares and the growing concentrations in many industries. Their model contributes to a literature that analyzes the heterogeneity of firm-level labor shares within industries and highlights the role of highly productive firms with below-average labor shares in driving the aggregate labor share down (e.g., Böckerman & Maliranta, 2012; Hartman-Glaser et al., 2019; Kehrig & Vincent, 2021). Within the superstar model, two potential mechanisms lead to subdued labor shares of large and highly productive firms. The first builds on market power and markups. Accordingly, superstar firms are able to translate their productive advantage into market power and significant markups, which consequently lower their labor shares. The second mechanism addresses fixed overhead labor costs. As superstar firms gain in size and market share due to their superior efficiency, they are able to spread fixed overhead labor costs over more output, which, in turn, lowers their labor share. While the mechanisms are not mutually exclusive, they have opposite implications from a competition perspective. In the first case, the rise of superstar firms must be seen as an indication of suboptimal functioning markets, whereas the latter would be a straightforward result of competition in which the more efficient firms prevail and grow.

While the first mechanism is tested empirically by Autor et al. (2020), the role of fixed overhead labor costs in explaining the below-average labor shares in highly productive firms is not yet assessed. This paper aims to fill this gap. As we discuss in the theoretical section of this study, the fixed-costs mechanism implies a non-linear relationship between TFP and labor shares that can be verified empirically. Furthermore, previous empirical studies – with the exception of Böckerman and Maliranta (2012) – almost exclusively focus on US firm-level data when describing the superstar phenomenon. Our study verifies whether the general link between firm size, total factor productivity, and lower labor share can be confirmed within the European context.



Using German IAB data, we show that firm size increases with total factor productivity in all industries. As a result, in the vast majority of industries, market shares are larger, the larger is the TFP. This is not just a characteristic of highly productive firms in the upper tail of the productivity distribution. Analyzing the size distribution by deciles of TFP confirms that this relationship holds across the entire distribution. Focusing on the relationship between labor shares and TFP, we find that total factor productivity and labor shares are negatively correlated, i.e., the larger the TFP, the lower the labor share. However, this relationship is less pronounced in service industries. Our empirical findings, thus, support the view that the superstar phenomenon is widespread across advanced economies.

In contrast, analyzing the relationship between TFP and labor shares by means of a second order polynomial, we find no evidence supporting the fixed-costs mechanism. Hence, the below-average labor shares of highly productive firms do not simply reflect higher (labor-) cost-efficiency. Eliminating this mechanism as a potential explanation for the lower labor shares shifts the focus toward other mechanisms discussed in the literature, such as excessive markups. Thus, our results support the view that the rise of very large, highly productive firms should be seen with some caution by policy makers and antitrust authorities.

## Acknowledgments

The authors gratefully acknowledge funding from the research grant “INNOMSME” (project number 01UI1802), provided by the German Federal Ministry of Education and Research. We are grateful to Pio Baake, Tomaso Duso, Alexander Kritikos, Jan Stede, as well as to two anonymous referees for very helpful comments and suggestions. This study uses the IAB Establishment Panel, Waves 1993-2017. DOI: [10.5164/IAB.IABBP9317.de.en.v1](https://doi.org/10.5164/IAB.IABBP9317.de.en.v1). Data access was provided via remote data execution (project number at IAB: fdz1243). All results were reviewed to prevent the disclosure of confidential information.

## Disclosure statement

No potential conflict of interest was reported by the author(s).

## Funding

This work was supported by the German Federal Ministry of Education and Research [01UI1802].

## Notes on contributors

*Alexander Schiersch* is a Senior Researcher at the German Institute for Economic Research. His research focuses on the impact of innovation, digitization and intangible capital on firm performance.

*Caroline Stiel* is a Senior Researcher at the German Institute for Economic Research. Her research focuses on the impact of firms' internal organization and ownership structure on firm performance.



## References

- Akerberg, D., Caves, K., & Frazer, G. (2015). Identification properties of recent production function estimators. *Econometrica*, 83(6), 2411–2451.
- Amaro, S., 2019. EU starts new preliminary probe into google and facebook's use of data. CNBC December 2nd 2019. <https://www.cnn.com/2019/12/02/european-commission-opens-probe-into-google-and-facebook-for-data-use.html>. last accessed: 19-May-2020.
- Amazon - Case. (2017). European commission antitrust case no. 40153 – E-book MFNS and related matters (Amazon): Summary of commission decision of 4 May 2017. *Official Journal of the European Union C*, 264, 7–10.
- Amazon Marketplace - Case, 2019. European commission antitrust case no. 40462 – Amazon marketplace: Opening of proceedings 17 July 2019. [https://ec.europa.eu/competition/antitrust/cases/dec\\_docs/40462/40462\\_6210\\_9.pdf](https://ec.europa.eu/competition/antitrust/cases/dec_docs/40462/40462_6210_9.pdf). last accessed: 20-May-2020.
- Andrews, D., Criscuolo, C., & Gal, P., 2015. Frontier firms, technology diffusion and public policy: Micro evidence from OECD countries. OECD Productivity Working Papers 2.
- Andrews, D., Criscuolo, C., & Gal, P., 2016. The best versus the rest: The global productivity slowdown, divergence across firms and the role of public policy. OECD Productivity Working Papers 5.
- Andrews, D., Criscuolo, C., & Gal, P., 2019. The best versus the rest: Divergence across firms during the global productivity slowdown. CEP Discussion Paper 1645.
- Android - Case, G. (2019). European commission antitrust case no. 40999 – Google android: Summary of commission decision of 18 July 2018. *Official Journal of the European Union C*, 402, 19–22.
- Argentesi, E., Buccirossi, P., Calvano, E., Duso, T., Marrazzo, A., & Nava, S., 2019. Merger policy in digital markets: An ex-post assessment. DIW Discussion Paper Series 1836.
- Autor, D., Dorn, D., Katz, L., Patterson, C., & Reenen, J. V. (2020). The fall of the labor share and the rise of superstar firms. *Quarterly Journal of Economics*, 135(2), 645–709.
- Autor, D., Dorn, D., Katz, L., Patterson, C., & Van Reenen, J. (2017a). Concentrating on the fall of the labor share. *American Economic Review: Papers & Proceedings*, 107(5), 180–185.
- Autor, D., Dorn, D., Katz, L., Patterson, C., & Van Reenen, J., 2017b. The fall of the labor share and the rise of superstar firms. NBER Working Paper Series No. 23396.
- Aw, B. Y., Roberts, M., & Xu, D. (2011). R&D investment, exporting, and productivity dynamics. *American Economic Review*, 101(4), 1312–1344.
- Bartelsman, E. J., & Zoltan, W., 2017. Measuring productivity dispersion. Tinbergen Institut Discussion Paper TI 2017-33/VI .
- Böckerman, P., & Maliranta, M. (2012). Globalization, creative destruction, and labour share change: Evidence on the determinants and mechanisms from longitudinal plant- level data. *Oxford Economic Papers*, 64(2), 259–280.
- Bond, S., Hashemi, A., Kaplan, G., & Zoch, P., 2020. Some unpleasant markup arithmetic: Production function elasticities and their estimation from production data. University of Oxford. Department of Economic. sDiscussion Paper Series 906.
- Bourguignon, F. (2017). World changes in inequality: An overview of facts, causes, consequences and policies. *CESifo Economic Studies*, 64(3), 345–370.
- Collard-Wexler, A., & De Loecker, J. (2015). Reallocation and technology: Evidence from the US steel industry. *American Economic Review*, 105(1), 131–171.
- De Loecker, J., Eeckhout, J., & Unger, G. (2020). The rise of market power an the macroeconomic implications. *Quarterly Journal of Economics*, 135(2), 561–644.
- De Loecker, J., & Warzynski, F. (2012). Markups and firm-level export status. *American Economic Review*, 102(6), 2437–2471.
- Detrixhe, J., 2019. Instead of breaking up facebook, the EU May force it to share its data. Quartz 17 May 2019. <https://qz.com/1622036/break-up-facebook-eus-margrethe-vestager-favors-making-it-share-data-instead/>. last accessed: 19-May-2020.
- Doraszelski, U., & Jaumandreu, J. (2013). R&D: Estimating endogenous productivity. *Review of Economic Studies*, 80(4), 1338–1383.

- EC, 2010. Commission regulation amending council regulation (EC) No 2223/96 as regards adaptations following the revision of the statistical classification of economic activities NACE revision 2 and the statistical classification of products by activity (CPA) in national accounts. Commission Regulation No 715/2010. European Commission.
- Elsby, M. E., Hobijn, B., & Sahin, A., 2013. The decline of the U.S. Labor Share. Brookings Papers on Economic Activity Fall.
- Facebook - Case, 2019. Bundeskartellamt case no. B6-22-16 – Facebook: Case summary and decision of 6 February 2019. Report. <https://www.bundeskartellamt.de/SharedDocs/Entscheidung/EN/Fallberichte/Missbrauchsaufsicht/2019/B6-22-16.pdf?blob=publicationFile&v=4>. last accessed: 20-May-2020.
- Fischer, G., Janik, F., Müller, D., & Schmucker, A. (2009). The IAB establishment panel: Things users should know. *Schmollers Jahrbuch: Journal of Applied Social Science Studies*, 129(1), 133–148.
- Flynn, Z., Gandhi, A., & Traina, J., 2019. Measuring markups with production data. Working Paper.
- Foster, L., Haltiwanger, J., & Syverson, C. (2008). Reallocation, Firm turnover, and efficiency: Selection on productivity or profitability? *American Economic Review*, 98(1), 394–425.
- Gandhi, A., Navarro, S., & Rivers, D. (2020). On the identification of gross output production functions. *Journal of Political Economy*, 128(8), 2973–3016.
- Google AdSense - Case, 2019. European commission antitrust case no. 40411: Commission fines Google €1.49 Billion for abusive practices in online advertising. Press Release 20 March 2019, Brussels. URL: [https://ec.europa.eu/commission/presscorner/detail/en/IP\\_19\\_1770](https://ec.europa.eu/commission/presscorner/detail/en/IP_19_1770). last accessed: 20-May-2020.
- Grullon, G., Larkin, Y., & Michaely, R. (2019). Are US industries becoming more concentrated? *Review of Finance*, 23(4), 697–743.
- Gutiérrez, G., & Philippon, T., 2018. How EU markets became more competitive than US markets: A study of institutional drift. NBER Working Paper No. 24700.
- Hartman-Glaser, B., Lustig, H., & Xiaolan, M. Z. (2019). Capital share dynamics when firms insure workers. *The Journal of Finance*, 74(4), 1707–1751.
- Intel - Case. (2009). European commission antitrust case COMP/C-3/37.990 – Intel: Summary of commission decision of 13 May 2009. *Official Journal of the European Union C*, 227, 13–17.
- Karabarbounis, L., & Neiman, B. (2014). The global decline of the labor share. *Quarterly Journal of Economics*, 129(1), 64–103.
- Karabarbounis, L., & Neiman, B. (2019). Accounting for Factorless Income. *NBER Macroeconomics Annual*, 33, 167–228.
- Kehrig, M., & Vincent, N. (2021). The micro-level anatomy of the aggregate labor share decline. *Quarterly Journal of Economics*, 136(2), 1031–1087.
- Mertens, M., 2019. Micro-mechanisms behind declining labour shares: Market power, production processes, and global competition. IWH-CompNet Discussion Papers No. 3.
- Microsoft - Case. (2007). European commission antitrust case no. COMP/C-3/37.792 – Microsoft: Summary of commission decision of 24 May 2004. *Official Journal of the European Union L*, 32, 23–28.
- Nolan, B., Richiardi, M., & Valenzuela, L. (2019). The drivers of inequality in rich countries. *Journal of Economic Surveys*, 33(4), 1285–1324.
- Parrotta, P., Pozzoli, D., & Pytlikova, M. (2014). Labor diversity and firm productivity. *European Economic Review*, 66, 144–179.
- Peters, B., Roberts, M., Vuong, V., & Fryges, H. (2017). Estimating dynamic R&D choice: An analysis of costs and long-run benefits. *RAND Journal of Economics*, 48(2), 409–437.
- Prüfer, J., & Schottmüller, C., 2017. Competing with Big Data. TILIEC Discussion Paper 6.
- Qualcomm - Case. (2018). European commission antitrust case no. 40220 – Qualcomm (Exclusivity Payments): Summary of commission decision of 24 January 2018. *Official Journal of the European Union C*, 269, 25–26.

- Richter, P. M., & Schiersch, A. (2017). CO2 emission intensity and exporting: Evidence from firm-level data. *European Economic Review*, 98, 373–391.
- Rodriguez, F., & Jayadev, A. (2013). The declining labor share of income. *Journal of Globalization and Development*, 3(2), 1–18.
- Rossi-Hansberg, E., Sarte, P. D., & Trachter, N. (2021). Diverging trends in national and local concentration. *NBER Macroeconomics Annual*, 35, 115–150.
- Rubinfeld, D., & Gal, M. (2017). Access barriers to Big Data. *Arizona Law Review*, 59, 339–381.
- Shopping - Case, G. (2018). European commission antitrust case no. 39740 – Google search (Shopping): Summary of commission decision of 27 June 2017. *Official Journal of the European Union C*, 9, 11–14.
- Stiel, C., Cullmann, A., & Nieswand, M. (2018). Do private utilities outperform local government-owned utilities? Evidence from German retail electricity. *German Economic Review*, 19(4) URL, 401–425.
- Stucke, M., & Grunes, A. (2015). Debunking the myths over big data and antitrust. *CPI Antitrust Chronicle*, 276, 1–10.
- Stuehmeier, T. (2018). The data-driven power of google and Co. A risk to competition? *Bertelsman Foundation Policy Brief*, 4, 1–7.
- Traina, J., 2018. Is aggregate market power increasing? Production trends using financial statements. New Working Paper Series No. 17, Stigler Center for the Study of the Economy and the State.
- Van Reenen, J., 2018. Increasing differences between firms: Market power and the macro-economy. CEP Discussion Paper 1576.

## Appendix A. Data and data access

We use the IAB Establishment Panel from the German Employment Agency, which is an annual survey of 16,000 establishments representative of over 2 million German establishments in all economic sectors. The survey's primary focus is on the firms' labor input, but it also contains balance sheet data as well as information on the firms' structure, investments, and innovation activities. It has been conducted since 1993 in West Germany and since 1996 in East Germany, with the latest accessible wave being, as of April 2020, the year 2017.

The data is subject to strict privacy conditions and can only be accessed in remote access via the web-interface JoSuA as well as on-site at the Research Data Centres of the Institute for Employment Research (IAB). Access is granted depending on the following conditions:

- Only researchers from scientific facilities assigned with independent scientific research can use the data. The eligible scientific facilities are universities and scientific institutions.
- Researchers must commit themselves to statistical confidentiality in accordance with Section 16 of the Federal Statistics Act (BStatG). To ensure data confidentiality some descriptive analyses (e.g., with low number of observations) are not allowed to be carried out.
- The data is granted project-specifically and can be accessed for three years (with possible extensions). The purpose of the study must be clearly outlined and must be related to the analysis of labor demand.
- Usage is free of charge.

A full description of the dataset, access conditions and the application procedure is given on the website of the Research Data Centre of the German Federal Employment Agency under DOI: 10.5164/IAB.IABBP9317.de.en.v1 .

## Appendix B

**Table B1.** Production function estimates.

Industries	Labor		Capital		Hansen	
	Coeff.	SE	Coeff.	SE	p-value	N
<b>Manufacturing</b>						
Food/beverages	0.694***	(0.025)	0.531***	(0.022)	1	3,636
Textiles	0.815***	(0.021)	0.334***	(0.017)	1	3,348
Wood/paper	0.764***	(0.022)	0.346***	(0.019)	1	3,650
Chemicals/pharma.	0.623***	(0.046)	0.458***	(0.037)	1	1,951
Rubber/plastics	0.835***	(0.030)	0.323***	(0.026)	1	4,348
Metal	0.870***	(0.017)	0.248***	(0.014)	1	7,419
Electronics /electric eq.	0.898***	(0.030)	0.224***	(0.028)	1	3,048
Mechanical engineering	0.971***	(0.025)	0.147***	(0.022)	1	4,554
Vehicle manufacturing	1.070***	(0.023)	0.089***	(0.020)	1	2,330
Others and repairing	0.826***	(0.016)	0.311***	(0.014)	1	4,032
<b>Utilities</b>	0.728***	(0.042)	0.397***	(0.043)	1	2,135
<b>Construction</b>	0.896***	(0.008)	0.237***	(0.007)	1	13,546
<b>Trade</b>						
Trade of motor vehicles	0.975***	(0.029)	0.172***	(0.025)	1	3,764
Wholesale trade	0.806***	(0.029)	0.213***	(0.024)	1	4,779
Retail trade	0.837***	(0.020)	0.240***	(0.017)	1	8,626
<b>Transport &amp; storage</b>						
Transportation	0.620***	(0.086)	0.374***	(0.067)	1	2,000
Storage/postal services	0.710***	(0.037)	0.348***	(0.036)	1	1,807
<b>Services</b>						
Tourism	0.828***	(0.010)	0.235***	(0.010)	1	4,328
Information/commu.	0.859***	(0.041)	0.256***	(0.032)	1	1,962
Finance/insurance	0.988***	(0.043)	−0.017	(0.025)	1	514
Real estate	0.873***	(0.100)	0.408***	(0.105)	1	1,533
Professional activities	0.812***	(0.009)	0.309***	(0.008)	1	7,441
Support services	0.725***	(0.018)	0.203***	(0.019)	1	4,781

Notes: \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ . The number of observations is lower than in Table B2, because the ACF method uses lagged variables as instruments. Consequently, some firm-year-observations drop out. Source: IAB Establishment Panel, 1993–2017, own calculations. DOI: 10.5164/IAB.IABBP9317.de.en.v1

**Table B2.** Regression of labor shares on TFP.

Industries	$\omega_{it}$		$\omega_{it}^2$		Constant		$R^2$	N
<b>Manufacturing</b>								
Food/beverages	0.352	(0.369)	− 0.077	(0.047)	0.375	(0.723)	0.04	4,570
Textiles	− 0.995	(0.750)	0.060	(0.059)	4.413	(2.368)	0.09	3,929
Wood/paper	1.532	(1.000)	− 0.125	(0.079)	− 4.113	(3.151)	0.04	4,164
Chem./pharma.	0.004	(0.393)	− 0.019	(0.036)	1.043	(1.038)	0.04	2,343
Rubber/plastics	0.515	(0.501)	− 0.048	(0.037)	− 0.679	(1.716)	0.04	5,015
Metal	5.202***	(0.890)	− 0.338***	(0.058)	− 19.432***	(3.437)	0.02	8,660
Electronics/eq.	− 0.465	(0.873)	0.023	(0.055)	3.014	(3.446)	0.16	3,664
Mechanical eng.	0.980	(1.340)	− 0.061	(0.075)	− 3.289	(5.951)	0.05	5,327
Others/repair.	1.039	(1.273)	− 0.087	(0.094)	− 2.502	(4.317)	0.04	4,867
<b>Utilities</b>	0.151	(0.232)	− 0.028	(0.020)	0.422	(0.672)	0.06	2,640
<b>Construction</b>	2.479***	(0.527)	− 0.162***	(0.033)	− 8.861***	(2.130)	0.01	16,308
<b>Trade</b>								
T. of motor veh.	0.124	(0.910)	− 0.014	(0.052)	0.452	(3.953)	0.10	4,625
Wholesale trade	1.642**	(0.528)	− 0.096**	(0.030)	− 6.438**	(2.305)	0.07	5,946
Retail trade	0.386	(0.280)	− 0.032	(0.017)	− 0.546	(1.134)	0.07	10,905
<b>Transp./storage</b>								
Transportation	0.600	(0.428)	− 0.061	(0.034)	− 0.661	(1.343)	0.03	2,714
Storage/post.	0.725	(0.496)	− 0.064	(0.038)	− 1.436	(1.615)	0.04	2,408
<b>Services</b>								
Tourism	0.856	(1.588)	− 0.052	(0.110)	− 2.879	(5.705)	0.01	5,809
Info./commu.	− 0.196	(1.137)	0.015	(0.073)	1.089	(4.413)	0.09	2,592
Real estate	− 0.499**	(0.183)	0.048*	(0.022)	1.622***	(0.391)	0.04	1,936
Professional act.	− 1.460	(1.021)	0.114	(0.072)	5.174	(3.601)	0.04	9,308
Support serv.	0.259	(0.307)	− 0.020	(0.017)	− 0.319	(1.349)	0.25	6,347

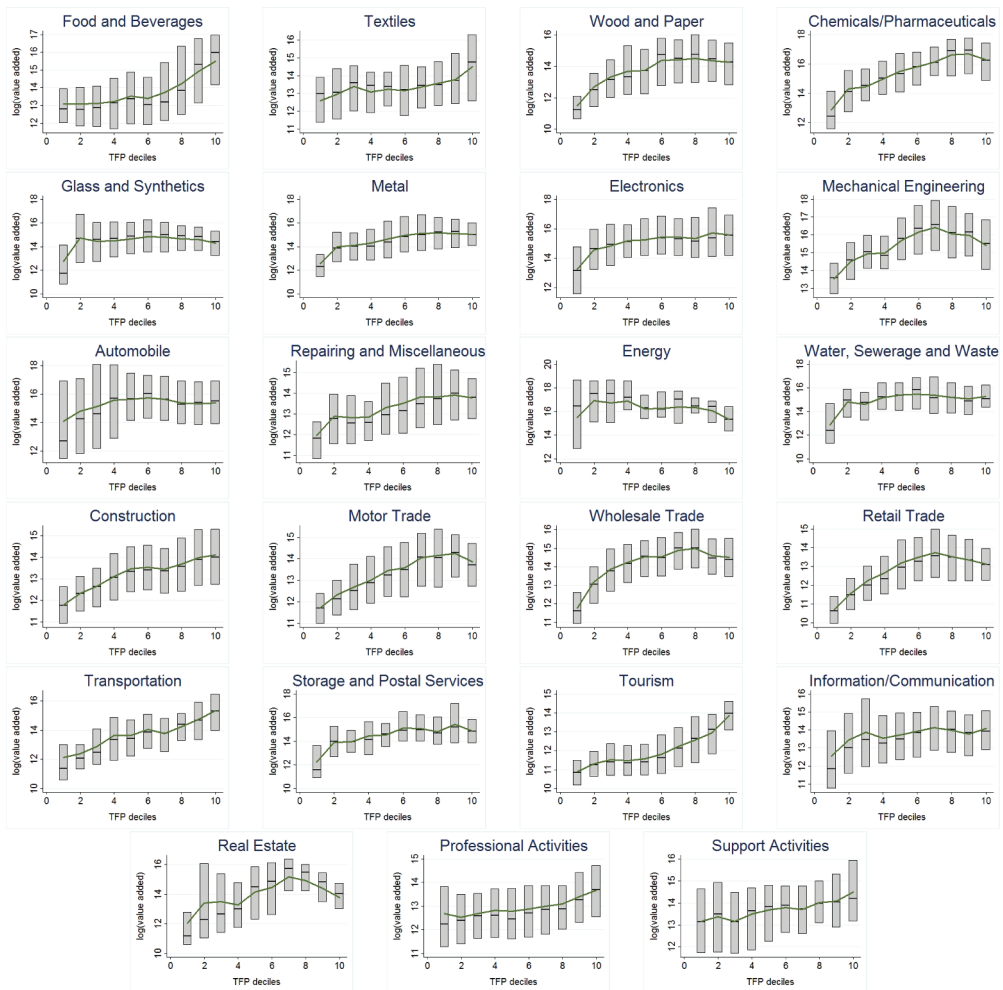
Notes: \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.001$ . Parentheses contain block-bootstrapped standard errors with 1,999 replications. All OLS calculations include year dummies and dummies for the 2-digit industries. The financial industry is excluded because of its insignificant production function coefficients. Source: IAB Establishment Panel, 1993–2017, own calculations. DOI: 10.5164/IAB.IABBP9317.de.en.v1

**Table B3.** Regressions with markup-adjusted TFP.

Industry	Market share		Labor share				
			Nonlinear effects				
	Linear		Linear	p10	p50	p90	
	(1)		(2)	(3)	(4)	(5)	
<b>Manufacturing</b>							
Food/beverages	0.005***	(0.001)	– 0.095***	(0.018)	0.069 +	– 0.068 +	– 0.234 +
Textiles	0.005***	(0.001)	– 0.100***	(0.017)	– 0.074	– 0.112	– 0.144
Wood/paper	0.004***	(0.001)	0.000	(0.024)	0.003	– 0.003	– 0.007
Chemicals/pharma.	0.010*	(0.005)	– 0.108***	(0.024)	– 0.084	– 0.113	– 0.138
Metal	0.002***	(0.000)	0.010	(0.017)	0.022	0.006	– 0.008
Electronics /electric eq.	0.006***	(0.001)	– 0.078**	(0.025)	– 0.083	– 0.075	– 0.068
Mechanical engineering	0.004***	(0.001)	– 0.042*	(0.018)	– 0.042	– 0.042	– 0.042
Others and repairing	0.003***	(0.001)	– 0.015	(0.022)	0.029	– 0.023	– 0.068
<b>Utilities</b>	0.000	(0.001)	– 0.068***	(0.016)	– 0.040	– 0.078	– 0.116
<b>Construction</b>	0.001***	(0.000)	– 0.016	(0.012)	– 0.011	– 0.017	– 0.023
<b>Trade</b>							
Trade of motor vehicles	0.004***	(0.001)	– 0.065***	(0.019)	– 0.100	– 0.051	– 0.015
Wholesale trade	0.002***	(0.000)	– 0.016	(0.014)	0.013 +	– 0.030 +	– 0.064 +
Retail trade	0.001**	(0.000)	– 0.081***	(0.012)	– 0.067	– 0.085	– 0.098
<b>Transport &amp; storage</b>							
Transportation	0.002*	(0.001)	– 0.047	(0.028)	0.016 +	– 0.064 +	– 0.130 +
Storage/postal services	0.001	(0.001)	– 0.052**	(0.017)	0.005 +	– 0.057 +	– 0.117 +
<b>Services</b>							
Tourism	0.003*	(0.001)	0.086***	(0.023)	0.033 +	0.128 +	0.200 +
Information/commu.	0.000	(0.002)	0.015	(0.021)	– 0.026	0.031	0.074
Real estate	0.001	(0.001)	– 0.078***	(0.018)	– 0.120	– 0.067	– 0.030
Professional activities	0.002*	(0.001)	0.021	(0.011)	– 0.006 +	0.025 +	0.057 +
Support services	0.008**	(0.003)	– 0.021*	(0.009)	– 0.028	– 0.021	– 0.014

Notes: \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.001$ . OLS estimations with block-bootstrapped standard errors in parentheses. TFP adjusted for firm-level markups according to equation (7). Coefficients for the market shares are obtained from estimating equation (3). The marginal effects for the labor shares in columns (3) to (5) are obtained from estimating equation (4) and computing the marginal effect for the p10, p50, and p90 quantiles of the TFP distribution using equation (5). The coefficients  $\hat{\gamma}_1$  and  $\hat{\gamma}_2$  from equation (4) are not significant at  $p < 0.05$  unless specified with "+". The financial industry is excluded because of its insignificant capital coefficient and the motor vehicle manufacturer because of its implausible labor coefficient of more than one. All firm-level markup estimates in the rubber/plastics industry were negative, so that the TFP could not be adjusted. Source: IAB Establishment Panel, 1993–2017, own calculations. DOI: 10.5164/IAB.IABBP9317.de.en.v1

## Appendix C



**Figure C1.** Value added by deciles of the TFP distribution by detailed industry. Note: The bars are defined by the interquartile range of value added. Each bar includes a dash that marks the median. The solid lines depict the means. TFP estimated by means of the ACF approach. Source: IAB Establishment Panel, 1993–2017, own calculations. DOI: 10.5164/IAB.IABBP9317.de.en.v1