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Testing the Superstar Firm Hypothesis

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Abstract

The superstar firms model provides a compelling explanation for two simultaneously occurring phenomena: the rise of concentration in industries and the fall of labor shares. Our empirical analysis confirms two of the underlying assumptions of the model: the market share increases and the labor share decreases with increasing firm-level total factor productivity, providing support for the superstar firms' hypothesis. However, we find no evidence for the underlying mechanism of the model, the distribution of fixed labor costs. Instead, we observe increasing returns to scale that also explain lower labor shares of larger firms.

Keywords: superstar firms, total factor productivity, labor share, market share, firm size

JEL classification: D24, E20, L11

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1. Introduction

An increasing number of studies suggest a rise of market power and a growing concentration in many economic sectors (Grullon et al., 2019; De Loecker et al., 2018; Rossi-Hansberg et al., 2018; VanReenen, 2018).¹ Simultaneously, the literature discusses the potential reasons for the shrinking share of labor in GDP and rising inequality in most western economies (Mertens, 2019; Nolan et al., 2018; Bourguignon, 2017; Karabarbounis and Neiman, 2014; Rodriguez and Jayadev, 2013; Elsby et al., 2013).

Autor et al. (2017a,b) have developed the widely recognized superstar model that links both observations and provides a possible explanation for them. This 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. Because of their size, these firms are able to spread fixed overhead costs, especially fixed labor costs, over more output, thus having lower labor shares. Superstar firms are therefore the channel linking the growing concentration with the falling labor share that is observed at the industry level.

In their empirical analyses, Autor et al. (2017a,b) focus on the negative relationship between concentration of industries and respective labor shares predicted by their model. Using a variety of different datasets, their analyses provide evidence for a negative correlation between various sector level concentration indicators and the labor shares at the industry level. However, neither the existence of superstar firms nor the presumed link between a firms' productivity, its size, and its labor share, nor the assumed mechanism of the model are directly tested by Autor et al. (2017a,b). To the best of our knowledge, this is also not tested so far by other studies. In the absence of this evidence, superstar firms cannot be identified as the driving force behind the reduced form observation of a positive correlation between concentration and the declining labor share at the industry level.

This paper aims to fill this gap. Specifically, we test two of the main propositions explicitly or implicitly used in the superstar model of Autor et al. (2017a,b): (I) The larger the total factor productivity (TFP) of firms, the larger they are and the higher their market shares; (II) the larger the TFP of firms, the lower their labor shares. Furthermore, we

¹Whether increasing concentration, growing mark-ups, and a reduction of competition intensity is a general phenomenon of western economies is still debated (Traina, 2018; Gutiérrez and Philippon, 2018).

argue that the mechanism used by the model has a testable implication. We 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 of the superstar model is correct. We then empirically test whether we find empirical support for such a relationship.

Our analysis uses German firm level data. Across a large number of different sectors of the 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 TFP distribution, have the highest value added and the lowest labor shares. While this finding supports two of the basic proposition of the superstar hypothesis, our analysis finds no evidence for the underlying mechanism the model proposes. Increasing returns to scale seem to be a better explanation for the superstar firms' low labor shares.

The remainder of the paper is organized as follows. Section 2 briefly describes the model and the approach to test the propositions, while section 3 presents the results. The last section concludes.

2. The superstar model

2.1. Propositions of the superstar model

The superstar model of [Autor et al. \(2017a,b\)](#) uses a standard Cobb-Douglas production function with constant or decreasing returns to scale.² The model requires the assumption 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). Labor elasticity (α_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. However, firms differ with respect to their total factor productivity (Ω_i) ([Autor et al., 2017a](#), p.181). Within the model, firm size is increasing with Ω_i ,³ which leads to the proposition that market shares are larger, the more productive the companies are. This important nexus is theoretically

²For a detailed presentation of the model, we refer to Appendix A in [Autor et al. \(2017b\)](#).

³See Eq. 9 in Appendix A in [Autor et al. \(2017b\)](#), p.52).

established by Autor et al. (2017a,b), but - to the best of our knowledge - not been empirically verified. Thus, the first proposition to be empirically tested is

Proposition 1: Firms are larger and capture a larger share of the market the larger their TFP.

Labor share is defined as $S_i = wL_i/(PY)_i$, with nominal value added as denominator. This is identical to $S_i = wV_i/(PY)_i + wF/(PY)_i$. Due to model assumptions, the first ratio is constant across all firms and identical to the labor elasticity (α_L). If firms are able to exploit market power, markups (price to marginal cost ratio) are different from 1 and the labor share can also be written as (Autor et al., 2017a, p.181):

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

We follow the authors and assume monopolistic competition, which has the consequence that "the markup is the same across firms in an industry" (Autor et al., 2017a, p.181). Because $\mu_i = \mu$ within an industry, the first term in Eq. 1 must be constant across all firms. In contrast, the value of the second component, the ratio of fixed labor over value added, is decreasing in value added. Because value added increases with Ω_i , the superstar 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

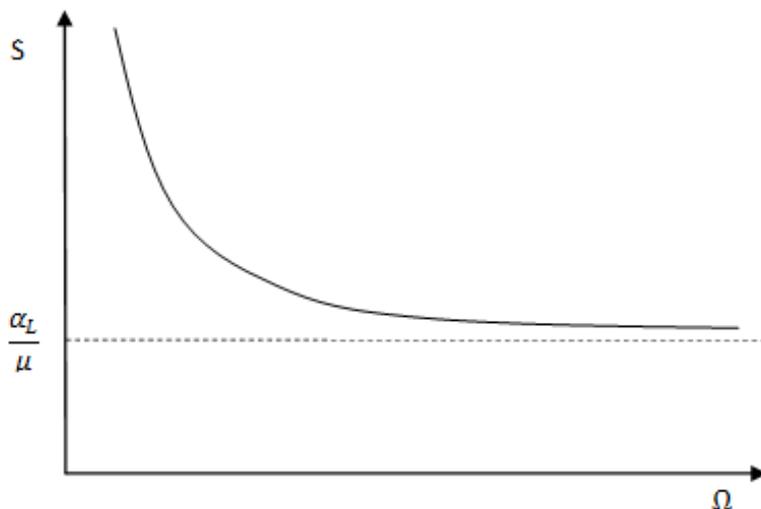
While the previous section focusses on two testable assumptions of the superstar model, this sections describes the mechanism that the model employs, shows its testable implication, and discusses an alternative reason for lower labor shares of large firms.

Spreading fixed costs is the main mechanism behind declining labor shares. Although not discussed by Autor et al. (2017a,b), Eq. 1 implies what the relationship between labor shares and TFP in general has to look like. As depicted in Figure 1, it must be a non-linear relationship with negative marginal effects that are decreasing in magnitude with increasing TFP. In fact, the marginal effect must converge towards zero as the labor share converges toward α_L/μ 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, due to an increase in TFP. In contrast, the premium on α_L/μ due to $wF/(PY)_i$ is already minimal for large firms, i.e. highly productive 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, whereas the marginal effects at the left tail of the TFP distribution must be larger than at the right tail of the TFP distribution.

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



The superstar model assumes constant or decreasing returns to scale. If increasing returns to scale would apply instead, output growth disproportionately with increasing inputs. Consequently, the labor share would be lower, the larger firms are, even without overhead fixed costs. In such cases, Proposition I and II would still hold because the highly productive and large firms, the superstar firms, would still have higher market shares and lower labor shares. Yet, the reason for that would be the increasing returns to scale instead of the spreading of fixed costs.

3. 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 et al., 2009).⁴ Our dataset covers the period 1996 to 2016. In 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. All monetary values are deflated using deflator time series provided by the Federal Statistical Office at the two-digit NACE industry level. The descriptive statistics of the variables are provided in Table B.1.

The firms' TFP is estimated by means of the control function approach of Akerberg et al. (2015) using a standard Cobb-Douglas production function. 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).⁵

Autor et al. (2017a,b) 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.⁶ We test proposition I 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

$$ms_{it} = \frac{P_{it}Y_{it}}{\sum_i P_{it}Y_{it}} = \beta_0 + \beta_1\omega_{it} + \tau_t + \eta_s + \epsilon_{it}, \quad (2)$$

where ms_{it} is the firm's market share in the industry, ω_{it} is the logged TFP at time t of firm i , τ_t are time dummies, η_s are sector fixed effects at the NACE 2-digit level, and ϵ_{it} is the error term. The errors are clustered at the firm-level and are robust to both serial correlation and heteroscedasticity.

Proposition II is tested using the subsequent estimations:

⁴The data is owned by Federal Employment Agency and subject to strict privacy policy but data access is free of charge. For a detailed description of data access see A.

⁵Table B.3 in the Appendix shows the results of the production function estimations

⁶We follow the literature by using percentiles or deciles for separating the top productive firms. See, among others, Andrews et al. (2015, 2016); Bartelsman and Zoltan (2017). Due to data limitations, we must use the top decile.

$$S_{it} = \frac{wL_{it}}{P_{it}Y_{it}} = \gamma_0 + \gamma_1\omega_{it} + \tau_t + \eta_s + u_{it}. \quad (3)$$

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 Eq. 3 is extended by the term $\gamma_2\omega_{it}^2$ when empirically verifying Proposition III. The marginal effect of TFP on the labor share then depends on the TFP distribution and is given by

$$\theta_{it} = \gamma_1 + 2\gamma_2\omega_{it} \quad (4)$$

4. Results

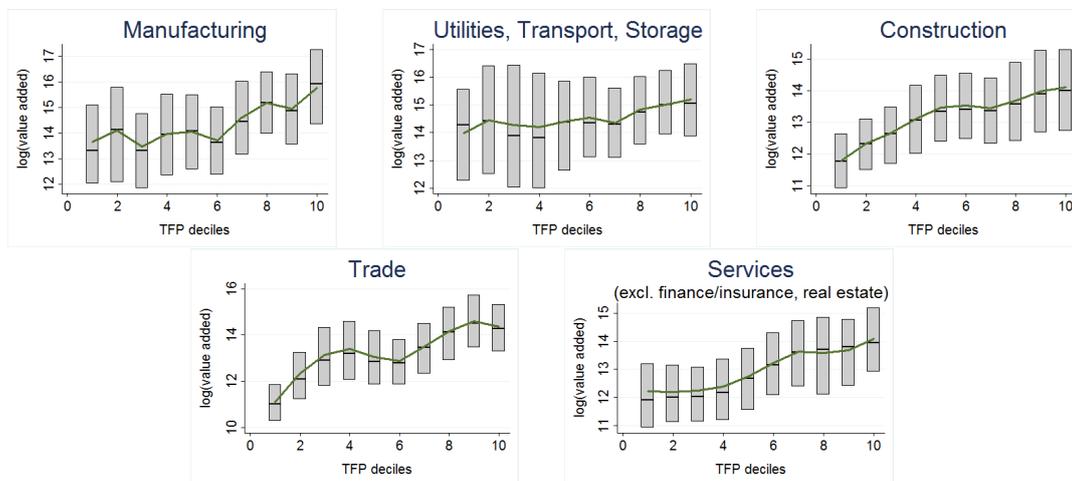
We start by analyzing whether the main result of Autor et al. (2017a,b), i.e. the negative correlation between the labor shares and industry concentration, is also observable in our data. Indeed, we find that industry concentration, measured by the aggregate market share of the top 20 firms (CR20), is negatively correlated with the aggregate labor share in that industry.^{7,8} The results hold both in levels and the 5-year-differences specification that are also employed by Autor et al. (2017b). Figure 2 addresses the first part of proposition I and presents the relationship between firm size and TFP at 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. We find that the superstar firms, i.e., the firms in the top decile of the TFP distribution, 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 increases 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.⁹ This supports the assumption of Autor et al. (2017a) regarding the nexus between firm size and TFP.

⁷See B.2 in the Appendix

⁸Besides 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.

⁹See Figure C.1 in the Appendix for a more detailed analysis.

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.

Using regression analysis, we test then the second part of proposition I of the model. Column (1) of Table 1 contains the marginal effects of a change in total factor productivity on the market share.¹⁰ The coefficients are positive and significant in 15 of the 21 industries, showing that the market share indeed increase 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 1 address proposition II. 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, so that relative savings on labor costs from fixed labor might be less important as firm size increases. In the other sectors, the labor share reacts quite

¹⁰We exclude the sectors 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 B.3 in the Appendix.

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.

Table 1: Regressions of market shares and labor shares on TFP

industry	market shares		labor shares			returns to scale (6)	
	linear (1)		linear (2)	nonlinear effects			
				p10 (3)	p50 (4)	p90 (5)	
manufacturing							
food/beverages	0.010*** (0.002)		-0.240*** (0.032)	-0.147	-0.199	-0.282	1.225
textiles	0.013*** (0.003)		-0.246*** (0.033)	-0.306	-0.262	-0.201	1.149
wood/paper	0.006*** (0.001)		-0.039 (0.050)	0.054	-0.042	-0.125	1.110
chemicals/pharma.	0.017* (0.008)		-0.193*** (0.037)	-0.172	-0.188	-0.208	1.081
rubber/plastics	-0.004*** (0.001)		-0.126*** (0.033)	-0.083	-0.113	-0.146	1.158
metal	0.002* (0.001)		0.024 (0.040)	0.236 ⁺	0.082 ⁺	-0.080 ⁺	1.118
electronics /electric eq.	0.007*** (0.002)		-0.111* (0.046)	-0.130	-0.111	-0.092	1.122
mechanical engineering	0.008*** (0.001)		-0.100** (0.037)	-0.065	-0.105	-0.134	1.118
others and repairing	-0.001 (0.002)		-0.138** (0.051)	-0.062	-0.119	-0.184	1.137
utilities	-0.004 (0.003)		-0.162*** (0.030)	-0.122	-0.152	-0.189	1.125
construction	0.003*** (0.001)		-0.074** (0.026)	0.060 ⁺	-0.026 ⁺	-0.121 ⁺	1.133
trade							
trade of motor vehicles	0.008*** (0.002)		-0.118*** (0.031)	-0.105	-0.116	-0.127	1.147
wholesale trade	0.003** (0.001)		-0.049* (0.022)	0.066 ⁺	-0.036 ⁺	-0.129 ⁺	1.019
retail trade	0.001** (0.000)		-0.118*** (0.018)	-0.078	-0.112	-0.141	1.077
transport & storage							
transportation	0.006** (0.002)		-0.126* (0.051)	-0.049	-0.117	-0.188	0.994
storage/postal services	0.005* (0.002)		-0.109** (0.035)	-0.025	-0.086	-0.166	1.058
services							
tourism	0.014*** (0.003)		0.114* (0.047)	0.151	0.119	0.080	1.063
information/commu.	-0.010 (0.010)		0.042 (0.049)	0.027	0.047	0.060	1.115
real estate	-0.004 (0.003)		-0.117*** (0.031)	-0.197 ⁺	-0.105 ⁺	-0.050 ⁺	1.281
professional activities	-0.002 (0.002)		0.154*** (0.037)	0.054	0.149	0.249	1.121
support services	0.008** (0.002)		-0.086*** (0.020)	-0.057	-0.080	-0.108	0.928

Notes: Standard errors are clustered at the firm-level and are robust to serial correlation and heteroscedasticity. Coefficients for the market shares are obtained from estimating equation (2). The marginal effects for the labor shares in columns (3) to (5) are obtained from estimating equation (3) and computing the marginal effect for the p10, p50, and p90 quantile of the TFP distribution using equation (4). The coefficients $\hat{\gamma}_1$ and $\hat{\gamma}_2$ from equation (3) are not significant at $p < 0.05$ unless specified with "+". Detailed regression results for equation (3) are given in the Appendix. Column (6) contains the sum of the labor and capital coefficient from the production function estimation. All coefficients are significant at $p < 0.05$ or higher. Detailed regression results are given in the Appendix. 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.

As outlined in section 2.2, the mechanism employed in the superstar model requires that the negative marginal effect of TFP on labor share is stronger at the lower tail of the TFP distribution and should continuously decrease in magnitude as we move towards 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 1. They contain the marginal effects at the tenth, the fiftieth, and the ninetieth quantile of the TFP distribution.

The nonlinear specification's first and second-order coefficients are significantly different from zero only in 4 out of 23 industries, marked by "+" in the table.¹¹ 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 for superstar firms. Both the insignificance in most industries and the opposite trend of the marginal effects across the TFP distribution contradict the mechanism assumed by the model, which stresses the role of fixed 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 III is rejected by the empirical results. Thus, our results speaks against the mechanism proposed by the model of [Autor et al. \(2017a,b\)](#). Fixed cost does not seem to be the main explanation for the superstar firms' low labor shares.

As outlined in subsection 2.2, increasing returns to scale would also lead to lower labor shares for large firms *and* explain the stronger marginal effects at the right tail of the TFP. Column (6) of Table 1 contains the returns to scale of production.¹² With two exceptions, we find increasing returns to scale in all industries. Consequently, lower labor shares among large firms could be driven by the fact that their input usage increases at a slower rate than output growth. Given the link between firm size and productivity established by proposition (I), this is a more probable explanation for the superstar firms' low labor shares.

5. Conclusion

According to the model of [Autor et al. \(2017a,b\)](#), the shrinking of the labor shares and the growing concentration in many industries are caused by the rise of superstar firms. These firms are characterized by superior productivity and low labor shares. Due to these

¹¹Detailed regression results are provided in Table B.4 of the Appendix.

¹²The underlying production function coefficients are provided in Table B.3 in the Appendix.

characteristics, they gain in size and market shares, which increases concentration while driving down the average labor share at industry level.

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 an important implication for economic policy: According to the model, the simultaneous occurrence of both phenomena is not an indication of market failure. Instead, competition forces less productive firms out of the market and allows the highly productive firms to gain market shares. Hence, concentration is the result of a fierce(r) competition. Lower labor shares are also not due to market power on the input side or excess returns of the companies due to weaker competition, it is just higher cost efficiency of highly productive firms—which become more important and thus drive down average labor shares. Hence, what is observed with respect to concentration and labor shares is rather a healthy development than problematic—given that the model is right.

While [Autor et al. \(2017a,b\)](#) provide compelling empirical evidence for a negative correlation between the concentration in industries and their labor shares, empirical evidence regarding the assumptions that the superstar model builds upon are missing. Besides empirically verifying these assumptions, we also tests the mechanism that is at the core of the superstar model and responsible for lower labor share of highly productive firms.

Using IAB data for Germany, we show that firm size increases with productivity in all industries. As a result, in the vast majority of industries, market shares are larger, the larger the TFP. This is not just a characteristic of superstar 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. The empirical findings of this paper, thus, support two of the underlying propositions of the superstar model.

Within the superstar model, more productive, and therefore larger, firms have lower labor shares because they are able to spread fixed overhead labor costs, which are assumed to be identical for all firms within the model, over more output. We discuss in the theoretical section of this study, that this mechanism implies a non-linear relationship between

TFP and labor shares. Using a second order polynomial, the analysis finds no evidence for such relationship and, hence, no support for the mechanism proposed by [Autor et al. \(2017a,b\)](#).

An alternative explanation for lower labor shares of highly productive large firms could be increasing returns to scale. In fact, the empirical results support such explanation. We find increasing returns to scale in nearly all industries. Given the positive link between firm size and TFP, the superstar firms' low labor shares could thus be due to input usage increasing at a slower rate than output growth, leading to declining labor shares in firm size and TFP.

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Declaration of Interest

Declarations of interest: none.

Other

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.

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 original 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 currently 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 have to 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 has to 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 [10.5164/IAB.IABBP9317.de.en.v1](https://www.iab.rwth-aachen.de/en/v1).

Appendix B Tables

Table B.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
ms_{it}	market share	0.0000	0.0042	0.0004	0.0162	0.0219	132,134

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

	CR20	Constant	R^2	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: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Parenthesis contain standard errors. Standard errors were clustered at industry-level and are robust to serial correlation and heteroscedasticity. All calculations include year dummies and dummies for industries. Dependent variable is the labor share.

Table B.3: Production function estimates

Industries	Labor		Capital		Hansen p-vau	N
	Coeff.	SE	Coeff.	SE		
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
vehicel 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
utilities	0.728***	(0.042)	0.397***	(0.043)	1	2,135
construction	0.896***	(0.008)	0.237***	(0.007)	1	13,546
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
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
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 observation is lower than in Table B.4, because the ACF method uses lagged variables as instruments. Consequently, some firms-year-observations drop out.

Table B.4: Regression of labor shares on TFP

Industries	ω_{it}	ω_{it}^2	Constant	R^2	N
food/beverages	0.352 (0.369)	-0.077 (0.047)	0.375 (0.723)	0.04	4,570
textiles	-0.995 (0.75)	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
chemicals/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/electric eq.	-0.465 (0.873)	0.023 (0.055)	3.014 (3.446)	0.16	3,664
mechanical engineering	0.980 (1.340)	-0.061 (0.075)	-3.289 (5.951)	0.05	5,327
vehicel manufacturing	3.357 (2.410)	-0.188 (0.133)	-14.416 (10.886)	0.12	2,770
others and repairing	1.039 (1.273)	-0.087 (0.094)	-2.502 (4.317)	0.04	4,867
utilities	0.151 (0.232)	-0.028 (0.020)	0.422 (0.672)	0.06	2,640
construction	2.479*** (0.527)	-0.162*** (0.033)	-8.861*** (2.130)	0.01	16,308
trade of motor vehicles	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
transportation	0.600 (0.428)	-0.061 (0.034)	-0.661 (1.343)	0.03	2,714
storage/postal services	0.725 (0.496)	-0.064 (0.038)	-1.436 (1.615)	0.04	2,408
tourism	0.856 (1.588)	-0.052 (0.110)	-2.879 (5.705)	0.01	5,809
information/commu.	-0.196	0.015	1.089	0.09	2,592

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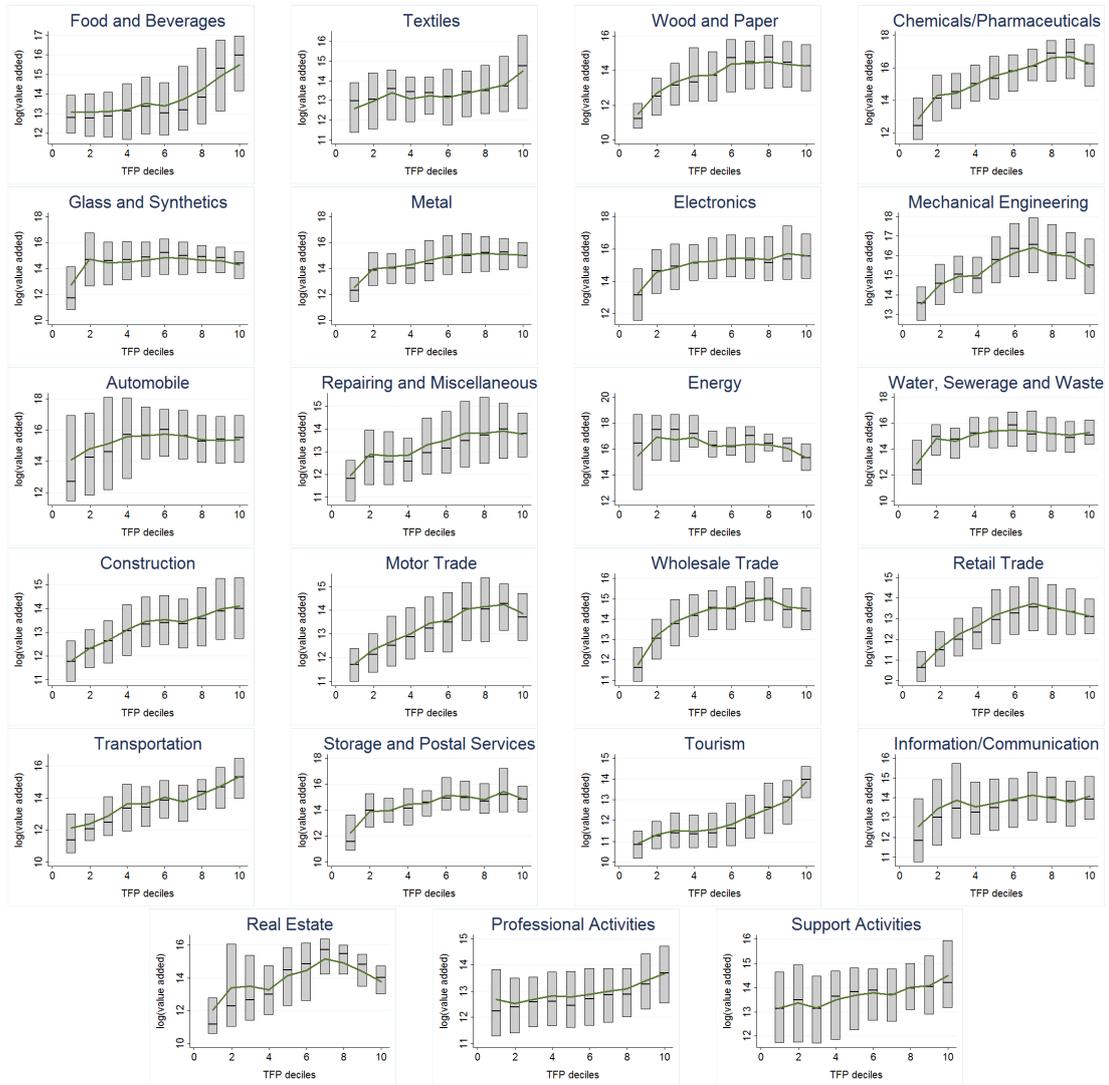
Table B.4: (continued)

Industries	ω_{it}	ω_{it}^2	Constant	R^2	N
	(1.137)	(0.073)	(4.413)		
real estate	-0.499**	0.048*	1.622***	0.04	1,936
	(0.183)	(0.022)	(0.391)		
professional activities	-1.460	0.114	5.174	0.04	9,308
	(1.021)	(0.072)	(3.601)		
support services	0.259	-0.020	-0.319	0.25	6,347
	(0.307)	(0.017)	(1.349)		

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$. Parenthesis contain standard errors. Standard errors were clustered at the firm-level and are robust to serial correlation and heteroscedasticity. All calculations include year dummies and dummies for the 2-digit industries. The financial industry is excluded because of its insignificant production function coefficients.

Appendix C Figures

Figure C.1: Value added by deciles of the TFP distribution by detailed industry



References

- Akerberg, D., Caves, K., Frazer, G., 2015. Identification Properties of Recent Production Function Estimators. *Econometrica* 83 (6), 2411–2451.
- Andrews, D., Criscuolo, C., Gal, P., 2015. Frontier firms, technology diffusion and public policy: micro evidence from OECD countries. OECD Productivity working papers.
- 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.
- 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.
- Bartelsman, E. J., Zoltan, W., 2017. Measuring productivity dispersion. Tinbergen Institute Discussion Paper TI 2017-33/VI.
- Bourguignon, F., 2017. World Changes in Inequality: An Overview of Facts, Causes, Consequences and Policies. Bank for International Settlement Working Papers Series No. 654.
- De Loecker, J., Eeckhout, J., Unger, G., 2018. The Rise of Market Power and the Macroeconomic Implications. NBER Working Paper Series No. 23687.
- 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.

- 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.
- Grullon, G., Larkin, Y., Michaely, R., 2019. Are US Industries Becoming More Concentrated? *Review of Finance*, 1–47.
- Gutiérrez, G., Philippon, T., 2018. How EU Markets Became More Competitive Than US Markets: A Study of Institutional Drift. NBER Working Paper No. 24700.
- Karabarbounis, L., Neiman, B., 2014. The Global Decline of the Labor Share. *Quarterly Journal of Economics* 129 (1), 64–103.
- Mertens, M., 2019. Micro-mechanisms Behind Declining Labour Shares: Market Power, Production Processes, and Global Competition. IWH-CompNet Discussion Papers No. 3.
- Nolan, B., Richiardi, M., Valenzuela, L., 2018. The Drivers of Inequality in Rich Countries. MPRA Paper No. 89806.
- 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., 2018. Diverging trends in national and local concentration. NBER Working Paper No. 25066.
- 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.
- VanReenen, J., 2018. Increasing Differences between firms: Market Power and the Macro-Economy. CEP Discussion Paper 1576.