A Lost Productivity Potential? Firm-Level Evidence on Measuring Misallocation in the German Manufacturing Sector (2014-2022)

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A LOST PRODUCTIVITY POTENTIAL? FIRM-LEVEL EVIDENCE ON MEASURING MISALLOCATION IN THE GERMAN MANUFACTURING SECTOR (2014-2022)

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[1]The views expressed in this thesis are my own and do not necessarily represent the position, policies, or views of the Deutsche Bundesbank or its staff.

Contents

List of Abbreviations / Glossary

Abbreviation	Meaning
AG	Public Stock Corporation in Germany
C	Aggregated manufacturing sector NACE
CA–CM	Aggregated manufacturing sector classification in the national accounts
COVID-19	Coronavirus Disease 2019
CRS	Constant Returns to Scale
GDP	Gross Domestic Product
Destatis	German Federal Office of Statistics
EU	European Union
GmbH	Private limited liability company in Germany
GVA	Gross Value Added
H	Hypothesis
HK	Hsieh & Klenow (2009) framework
Industry 4.0	Fourth Industrial Revolution
ISIC	International Standard Industrial Classification
JANIS	Annual Financial Statements of Non-Banks in Germany — Statistics (Deutsche Bundesbank)
JANIS-ID	Unique anonymized firm identifier in the JANIS database
LP	Labour Productivity
MP	Marginal Product
MPC	Marginal Product of Capital
MPL	Marginal Product of Labour
MRP	Marginal Revenue Product
MRPC	Marginal Revenue Product of Capital
MRPL	Marginal Revenue Product of Labour
NACE	Statistical Classification of Economic Activities in the European Union
OECD	Organisation for Economic Cooperation and Development
OP	Olley–Pakes decomposition
OP cov.	Covariance term from Olley–Pakes decomposition
OP-gap	Olley–Pakes gap — difference between weighted and aggregate productivity
RDSC	Research Data and Service Center
RQ	Research Question
Raval	Flexible markup estimation method by Raval (2023)
SME	Small and Medium sized Enterprises
TFP	Total Factor Productivity
TFPQ	Quantity-based Total Factor Productivity
TFPR	Revenue-based Total Factor Productivity
UC	User Cost of Capital
US	United States
VA	Value Added
VGR	National Accounts from Destatis
WZ 2008	German Classification of Economic Activities (based on NACE Rev. 2) from 2008

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1. Introduction

Over the past decades, pronounced differences in total factor productivity (TFP) have emerged both across countries and across sectors, raising a central question: Is there a lost productivity potential? Are these disparities primarily driven by technological frontier gaps, or do they instead reflect inefficiencies in how capital and labour are allocated within economies? This question lies at the core of modern growth theory and is of immediate policy relevance, particularly in advanced economies such as Germany, where concerns about industrial competitiveness and long-term productivity growth are increasingly pressing.

The seminal framework of Hsieh and Klenow (2009) provides a compelling perspective: Using firm-level data for China and India, they demonstrate that much of aggregate productivity differences can be traced not to technological shortfalls, but to misallocation of resources between firms. Their analysis shows that when capital and labour are not allocated according to firms' relative marginal products (MRPs), aggregate output falls well below its potential. In contrast, the U.S. manufacturing sector, serving as a benchmark, appears closer to efficient allocation, which underscores the decisive role of institutional and structural factors in shaping productivity outcomes.

Although a growing literature highlights allocative efficiency as a key lever for productivity growth, empirical evidence remains limited for advanced economies and sectors dominated by small and medium enterprises (SMEs) - such as Germany's manufacturing base - when it comes to explaining the productivity puzzle following Calligaris, Del Gatto, Hassan, Ottaviano, and Schivardi (2018) measuring misallocation in the Italian manufacturing sector. This gap is especially notable given that Germany's manufacturing sector constitutes both the backbone of its national economy and a pillar of European industrial output. Gaining a deeper understanding of the extent to which productivity is constrained by misallocation provides not only theoretical insight but also practical guidance for industrial policy, competitiveness, and resilience strategies.

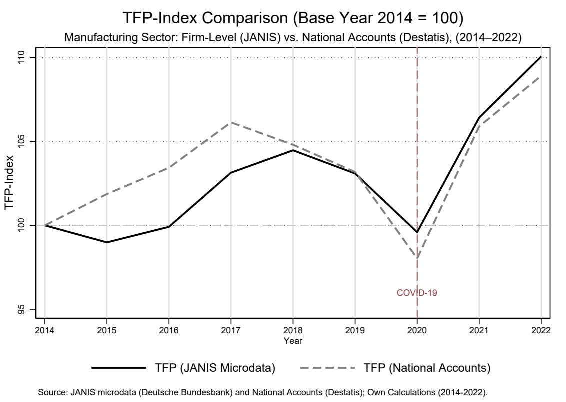


Figure 1: Total Factor Productivity (TFP): Macro- vs. Micro-Based Trends in German Manufacturing (2000–2022). Source: JANIS microdata and VGR (Deutsche Bundesbank, Destatis). Own calculations.

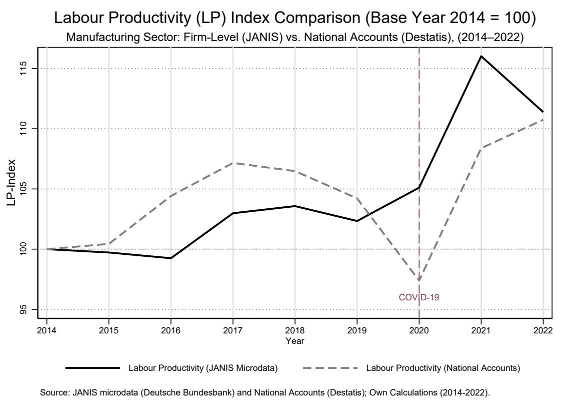


Figure 2: Labour Productivity (LP): Macro- vs. Micro-Based Trends in German Manufacturing (2000–2022). Source: JANIS microdata and VGR (Deutsche Bundesbank, Destatis). Own calculations.

Germany has experienced a marked slowdown in productivity growth despite advances in digitalization, capital deepening, and global trade integration (International Monetary Fund, 2012; Sachverständigenrat zur Begutachtung der gesamtwirtschaftlichen Entwicklung, Nationale Akademie der Wissenschaften Leopoldina, & acatech – Deutsche Akademie der Technikwissenschaften, 2025). Recent macroeconomic shocks such as the COVID-19 pandemic have accentuated the debates about resilience, industrial structure, and effective allocation of resources (de Vries, Erumban, & van Ark, 2021). Firm-level data offer a powerful lens for investigating these questions with much finer resolution than aggregate national accounts (VGR), capturing sharper responses to cyclical and structural shocks (see Figures 1 and 2).

This thesis addresses this gap using a unique empirical approach: By integrating misallocation measurement, reallocation analysis, and flexible input-specific markup estimation in one harmonized micro-macro dataset, new and nuanced insights can be gained, as well as input-specific, drivers of productivity. This triad of analytic approaches systematically explores how sector- and firm-level mechanisms, particularly under crisis shocks, alter productivity dynamics and identify critical bottlenecks for efficient resource use.

Against this empirical and policy background, the central research question of this thesis is as follows: To what extent has allocative efficiency and misallocation of inputs in German manufacturing changed between 2014 and 2022, and which sectoral and firm-level drivers shaped these developments, especially during the COVID-19 period? The following supporting research questions are addressed:

RQ1: How did allocative efficiency and misallocation in German manufacturing evolve between 2014–2022, particularly during the COVID-19 Pandemic? **RQ2:** Which firm-level and sectoral characteristics explain dispersion patterns, and how did the Covid-19 Pandemic influence them? **RQ3:** How did reallocation dynamics change during the COVID-19 Pandemic, and how are they linked to shifts in firm composition? **RQ4:** Do factor-specific markups (labour vs. materials) diverge during disruptions, indicating input-specific distortions?

From these questions, five hypotheses (H) emerge, each empirically testable and grounded in theoretical and policy contexts:

H1: TFPR dispersion increased over 2014–2022, especially during the COVID19 pandemic, implying an increase in allocative inefficiency. **H2:** Capital distortions contribute more to misallocation than labour distortions. **H3:** Misallocation is heterogeneous between sectors and firm sizes, with crises exacerbating inefficiencies. **H4:** The Covariance of within-firm and between-firm in terms of productivity weakened during the COVID-19 Pandemic, as incumbents retained market shares despite lower productivity. **H5:** Labour and material markups diverged more during disruptions, consistent with input-specific distortions.

To empirically assess these hypotheses and research questions, I construct a harmonized micro-macro dataset combining firm-level balance sheet data from the JANIS database (Research Data and Service Centre of the Deutsche Bundesbank, 2023) with sectoral aggregates from the German VGR (Statistisches Bundesamt (Destatis), 2025). This integration allows for novel derivations, such as capital user costs (UC), real deflators, and sector- and firm-level TFP benchmarks, fully aligned with official standards, thus strengthening both empirical reliability and policy relevance.

The unique contribution of this thesis lies in the combined use of three state-of-the-art empirical frameworks and harmonized microdata, enabling a richer diagnosis of productivity constraints and actionable insights for industrial policy. The findings will inform current debates on competitiveness, SME financing, and crisis response in the German manufacturing landscape.

The remainder of this thesis is organized as follows. Chapter 2. reviews theoretical foundations and recent advances. Chapter 3. introduces the data sources and the construction of analytical samples. Chapter 4. outlines the empirical frameworks. Chapter 5. presents the main findings and relates them to the literature. Chapter 6. synthesizes limitations, offers policy implications, and suggests avenues for future research.

2. Theoretical Framework

This chapter examines the theoretical foundations and recent advances in productivity research. It highlights key approaches to misallocation and demonstrates how the latest literature extends existing models, offering new perspectives on efficient resource use in advanced economies.

2.1 Recent Developments

While the framework of Hsieh and Klenow (2009) provides a tractable and widely applied model to quantify misallocation, recent literature has broadened the conceptual lens in several important directions. These contributions challenge key assumptions of the original model, refine measurement approaches, and provide deeper insights into the mechanisms by which resource misallocation arises and persists in advanced economies.

Technological Heterogeneity and Dynamic Efficiency. In the original Hsieh and Klenow (2009) framework, it is assumed that all firms within a sector share a common production technology and face the same input prices. However, research by Hopenhayn and Rogerson (2013) and Gopinath, Kalemli-Özcan, Karabarbounis, and Villegas-Sanchez (2017) highlights that firms differ not only in productivity levels but also in their capacity to adopt and implement new, capital-embodied technologies. Distortions thus reduce both static and dynamic efficiency, discouraging investments in more productive technologies (Andrews, Criscuolo, & Gal, 2016). This is particularly relevant for Germany, where digitalisation, Industry 4.0, and the energy transition create uneven investment responses across firms (Niehoff et al., 2022).

Frontier versus Laggard Firms. The literature on productivity leaders and laggards shows that aggregate productivity increasingly depends on the distributional dynamics within sectors. Andrews et al. (2016) document that productivity growth is concentrated among frontier firms, while most firms experience slow or no improvements. Berlingieri, Blanchenay, and Criscuolo (2024) show that the divergence between frontier and non-frontier firms has widened, driven by uneven access to finance, skills, and digital technologies. From a misallocation perspective, the reallocation channel—which should shift resources toward dynamic firms—is increasingly constrained (Gonzalez, Nuño, Thaler, & Albrizio, n.d.).

Market Power and Misallocation. De Loecker, Eeckhout, and Unger (2020) document a broad-based rise in markups across U.S. industries, linked to reduced business dynamism and lower responsiveness to shocks. Traina (2018) finds that rising markups depress factor shares and distort MRPs. TFPR dispersion, the core Hsieh and Klenow (2009) metric, may thus conflate pricing power with allocative inefficiency. Flexible markup estimation, such as Raval (2023), can help separate these effects.

Macro-Level Productivity Slowdowns. Bils, Klenow, and Malin (2018) argue that aggregate productivity estimates may conflate misallocation with measurement issues, such as quality-adjusted inputs or intangible capital. Restuccia and Rogerson (2013) model persistent distortions generating large macroeconomic effects, including lower TFP growth and weak reform responses. Micro-level misallocation is thus a structural feature with economy-wide consequences (Yang, 2021).

Institutional Frictions and Policy Distortions. Restuccia and Rogerson (2013) argue that policies often unintentionally favor less productive incumbents, through subsidies, tax breaks, or credit guarantees, while constraining dynamic entrants. Bartelsman, Haltiwanger, and Scarpetta (2013) show that the regulatory differences between countries explain a substantial variation in allocative efficiency. In Germany, sector-specific regulation, labour market dualism, and firm size-dependent policies can interact with technological shocks to amplify productivity gaps (Alecke & Mitze, 2023; Eichhorst & Tobsch, 2015; Heise & Porzio, 2022).

Capital Costs, Financial Frictions, and User Costs. Heterogeneity in capital UC, driven by differences in discount rates, depreciation structures, and risk premia, affects capital allocation (Syverson, 2011). Ignoring these differences biases MRP estimates, which is why I incorporate user cost estimates from VGR to better measure capital-based distortions (Hall & Jorgenson, 1967; Inklaar & Timmer, 2013).

Macroeconomic Shocks and Reallocation Bottlenecks. Acemoglu and Restrepo (2018) show that automation may amplify misallocation if institutions fail to facilitate reallocation. Evidence from Gopinath and Neiman (2014) and Dias, Marques, Richmond, et al. (2016) indicates that crises such as the Great Recession and the Eurozone crisis generated persistent distortions, as constrained or rigid firms could not optimally adjust input levels. This thesis extends this perspective to the COVID-19 Pandemic, testing whether misallocation intensified during the crisis years of the Pandemic.

Research Motivation. Central to the research question, I hypothesize that the sectoral spread of TFPR has increased over the observation period and that this increase has been particularly pronounced during the COVID-19 pandemic, indicating a rise in allocative inefficiency. Within the Hsieh and Klenow (2009) framework, the analysis further expects that capital distortions have contributed more strongly to observed misallocation than labour distortions, and that these distortions display significant heterogeneity across sectors and firm sizes with crisis-induced shocks exacerbating existing inefficiencies.

In addition, I anticipate that the reallocation of market shares toward more productive firms, as captured by the Olley and Pakes (1996) (OP)-covariance term from Altomonte and Di Mauro (2022), has weakened during the COVID-19 period, reflecting a decline in the contribution of reallocation to aggregate productivity growth. This reduction in the Olley and Pakes (1996)-gap is expected to coincide with shifts in the composition of firms, whereby incumbents retain market share despite lower productivity, while potential high-productivity entrants face barriers to expansion. Finally, I apply the flexible markup estimation method of Raval (2023),I hypothesize that labour and material markups have diverged more strongly during periods of economic disruption, signalling input-specific distortions related to policy measures such as short-time work schemes or to supply chain rigidities.

This multi-framework approach links microlevel distortions to macroeconomic performance, enabling a more nuanced and policy-relevant assessment of Germany's productivity constraints.

2.2 Hsieh & Klenow (2009)

A central element through which aggregate productivity differs between countries and over time is the efficiency of resource allocation among heterogeneous producers (Rogerson & Restuccia, 2004; Syverson, 2011). I follow the framework of Hsieh and Klenow (2009), which embeds firm heterogeneity into a static monopolistic competition model with Cobb–Douglas technology,

$$Y_{si} = A_{si} K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}, \tag{1}$$

where A_{si} denotes Hicks neutral TFP, and α_s is the sector-specific capital share. Under constant returns and perfect markets, factor inputs equalise productivity-weighted MPs within sectors in a closed economy (Hsieh & Klenow, 2009)[2] In the efficient benchmark, TFPR is constant across firms; dispersion reflects wedges such as credit constraints, rigid labour markets, or policy distortions (Banerjee & Duflo, 2005; Midrigan & Xu, 2014). Evidence for the Organization for Economic Cooperation and Development(OECD) member countries links the high spread of TFPR to the widening of the laggard frontier gaps (Andrews et al., 2016); in the German manufacturing context, persistent spread would support the view that misallocation is a structural source of productivity slowdown (Calligaris et al., 2018; Dias et al., 2016).

[2]Firm heterogeneity enters via A_{si}, with sectoral output aggregated using CES preferences ($\sigma > 1$) Dixit and Stiglitz (1977), allowing TFPR to serve as a diagnostic of allocative efficiency.

Quantity-based Productivity (TFPQ). According to the Cobb-Douglas specification, quantity-based TFP is

$$TFP_{Qsi} = \frac{Y_{si}}{K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}} = A_{si}, \tag{2}$$

measuring technological efficiency net of prices and demand (Solow, 1957; Syverson, 2011). While TFPQ dispersion reflects pure technological heterogeneity, it is rarely observable in multi-product industries due to missing physical quantities (Calligaris et al., 2018; De Loecker & Goldberg, 2014; Hsieh & Klenow, 2009). In such settings, TFPR is used instead, but conflates technology with prices; its dispersion therefore captures both allocative inefficiency and price variation (Calligaris et al., 2018; Hsieh & Klenow, 2014).

Revenue-based Productivity (TFPR). Revenue-based TFP measures nominal output per input unit,

$$TFPR_{si} = \frac{P_{si} Y_{si}}{K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}} = P_{si} A_{si}, \tag{3}$$

combining technological efficiency A_{si} with firm-specific prices P_{si} (Calligaris et al., 2018; Hsieh & Klenow, 2009). Under perfect competition with identical prices, $TFPR = TFPQ$; in practice, markups, product differentiation, and demand heterogeneity cause divergence (De Loecker & Goldberg, 2014; Foster, Haltiwanger, & Syverson, 2008; Hall, 1988; Melitz, 2003).

In the Hsieh and Klenow (2009) and Calligaris et al. (2018) framework, allocative efficiency implies equal $TFPR$ across firms within a sector,

$$TFPR_{si} = \overline{TFPR}_s \quad \forall i \in s,$$

ensuring equalized MRPs and optimal input allocation (Bartelsman et al., 2013; Rogerson & Restuccia, 2004). Deviations from this benchmark,

$$\ln\left(\frac{\overline{TFPR}_s}{TFPR_{si}}\right) \neq 0,$$

indicate firm-specific distortions—such as taxes, credit frictions, labour market rigidities, or policy-induced wedges (Midrigan & Xu, 2014; Restuccia & Rogerson, 2013). The variance of $\log(TFPR)$ serves as a sufficient statistic for misallocation Bartelsman et al. (2013); Restuccia and Rogerson (2013), though it may also reflect market power Syverson (2011). Higher dispersion signals greater inefficiency and unrealized productivity potential Andrews et al. (2016); Hsieh and Klenow (2009); for German manufacturing, persistent dispersion would be consistent with misallocation as a structural driver of the productivity gap Calligaris et al. (2018); Dias et al. (2016).

MRPs and TFPR Composition. In the Hsieh and Klenow (2009) framework with Cobb–Douglas technology and constant returns to scale,

$$Y_{si} = A_{si} K_{si}^{\alpha_s} L_{si}^{1-\alpha_s},$$

the marginal product of capital (MPC) is

$$\frac{\partial Y_{si}}{\partial K_{si}} = \alpha_s \frac{Y_{si}}{K_{si}},$$

which, multiplied by the firm-specific price P_{si}, gives

$$MRPC_{si} = \alpha_s \frac{P_{si} Y_{si}}{K_{si}}.$$

Analogously, the marginal product of labour (MPL) is

$$\frac{\partial Y_{si}}{\partial L_{si}} = (1-\alpha_s)\frac{Y_{si}}{L_{si}},$$

yielding

$$MRPL_{si} = (1-\alpha_s)\frac{P_{si}Y_{si}}{L_{si}}.$$

In an efficient factor market, MRPC and MRPL are equalized across firms Bartelsman et al. (2013); Rogerson and Restuccia (2004), which is equivalent to equalizing $TFPR_{i,s}$, since TFPR is a factor-share-weighted combination of MRPC and MRPL, makes it an indirect measure Calligaris et al. (2018); Hsieh and Klenow (2009).[3]

Distortions as Wedges in MPs. In the Hsieh and Klenow (2009) misallocation framework, firm-specific distortions appear as wedges between MRPs and factor prices,

$$\tau_{K,i} = \frac{MRPC_{si}}{r}, \quad \tau_{L,i} = \frac{MRPL_{si}}{w},$$

where r and w denote the capital rental rate across the economy and the wage rate (Restuccia & Rogerson, 2013; Rogerson & Restuccia, 2004). In an efficient allocation, $\tau_{K,i} = \tau_{L,i} = 1$ for all firms, that is, factor prices equal MRPs. Deviations from unity indicate distortions, such as credit constraints, regulatory frictions, or policy interventions Besley and Burgess (2004); Hsieh and Klenow (2014); Midrigan and Xu (2014), that prevent optimal use of input.

TFPR as Geometric Mean of Distorted Marginal Returns. In the Hsieh and Klenow (2009) framework, TFPR can be expressed as a factor-share-weighted geometric mean of the MRPC and MRPL,

$$TFPR_{si} \propto (MRPC_{si})^{\alpha_s} \cdot (MRPL_{si})^{1-\alpha_s},$$

where α_s is the sectoral capital elasticity (Bartelsman et al., 2013; Rogerson & Restuccia, 2004). This formulation aggregates input-specific distortions into a single measure of allocative efficiency, with the geometric mean ensuring proportional weighting by factor shares.

In the structural setup, the productivity at the firm-level A_{si} cancels out, so the variation in $TFPR_{si}$ reflects only the distortions (Calligaris et al., 2018; Hsieh & Klenow, 2014). Formally,

$$TFPR_{si} \propto \frac{(1+\tau_{si}^K)^{\alpha_s}}{(1-\tau_{si}^Y)},$$

where τ_{si}^K and τ_{si}^Y denote capital and output distortions (Andrews et al., 2016; Banerjee & Duflo, 2005). The dispersion of $\ln(TFPR_{si})$ within a sector thus serves as a sufficient statistic for misallocation, with a higher dispersion indicating greater potential TFP gains from reallocation (Calligaris et al., 2018; Dias et al., 2016).

Sectoral Allocative Efficiency Component (A_s). The sectoral allocation efficiency component A_s captures the extent to which aggregate productivity in a sector is shaped by the efficiency of resource allocation between firms. Assuming a CES aggregator with substitution elasticity $\sigma > 1$, aggregate TFP in sector s can be expressed as:

$$A_s = \left(\sum_i A_{si}^{\sigma-1}\left(\frac{\overline{TFPR}_s}{TFPR_{si}}\right)^{\sigma-1}\right)^{\frac{1}{\sigma-1}}, \tag{4}$$

[3] Persistent dispersion in MRPC or MRPL indicates input-specific distortions—such as capital market imperfections, wage rigidities, or sector-specific policies Andrews et al. (2016); Midrigan and Xu (2014)—and helps identify whether TFPR dispersion is driven mainly by capital or labour misallocation, thereby clarifying the sources of aggregate productivity differences.

where $A_{s,i}$ is the Hicks neutral productivity at the firm-level, $\overline{TFPR}_s$ denotes the TFPR sectoral benchmark, and $TFPR_{s,i}$ is the revenue productivity of the firm i (Calligaris et al., 2018; Hsieh & Klenow, 2009).

Reallocation term:

$$\frac{\overline{TFPR}_s}{TFPR_{si}} \tag{5}$$

This term measures the deviation of each firm's TFPR from the sectoral benchmark and therefore reflects the degree of misallocation (Calligaris et al., 2018; Rogerson & Restuccia, 2004). The CES aggregation framework highlights that sectoral productivity depends not only on technological fundamentals A_{si}, but also on the distribution of inputs across firms (Syverson, 2011). This can be re-expressed as a sectoral production function in logarithmic form:

$$\ln Y_s = \ln A_s + \alpha \ln K_s + (1-\alpha)\ln L_s, \tag{6}$$

where A_s summarizes the impact of allocation of resources within the sector on sectoral output. Persistent inefficiencies in A_s imply unrealized productivity potential, an aspect particularly relevant when investigating structural productivity gaps in advanced manufacturing sectors (Calligaris et al., 2018; Hsieh & Klenow, 2009).

Efficient Allocation (A_s^*). In the Hsieh and Klenow (2009) framework applied by Calligaris et al. (2018) for Italy, the counterfactual productivity level under perfect allocation is

$$A_s^* = \left(\sum_i A_{si}^{\sigma-1}\right)^{\frac{1}{\sigma-1}},$$

where all companies in sector s face identical input distortions, i.e. $TFPR_{si} = \overline{TFPR}_s$ for all i (Calligaris et al., 2018; Hsieh & Klenow, 2009).[4] In this benchmark, the CES reallocation term equals one. The gap $A_s^* - A_s$ quantifies the productivity loss from misallocation, while A_s/A_s^* measures the efficiency of the allocation of input within the sector.[5]

Factor Shares and Output Elasticities. In the Cobb–Douglas two–factor production framework, α_k and α_l denote the output elasticities of capital and labour. Under perfect competition, these elasticities correspond to factor income shares:

$$\alpha_k = \frac{r_K K}{VA}, \quad \alpha_l = \frac{wL}{VA}, \quad \alpha_k + \alpha_l = 1, \tag{7}$$

where r_K is the rental rate of capital, w the wage rate, and VA value added Calligaris et al. (2018); Hsieh and Klenow (2009).[6]

In empirical applications, sector-specific capital elasticities are often recovered as the residual from unity:

$$\alpha_s = 1 - \frac{\text{Labour Compensation}_{i,s}}{VA_{si}}, \tag{8}$$

where labour compensation includes wages, salaries, bonuses, and employer social contributions.[7]

[4] Typically applied in partial equilibrium with fixed factor prices; in general equilibrium, factor price adjustments imply that measured wedges are a lower bound on inefficiency (Acemoglu & Zilibotti, 2001; Gollin, 2002).

[5] Persistent distortions from policy, institutions, or financial frictions can be distinguished from transitory shocks linked to firm dynamics; cross-country evidence links higher TFPR dispersion to structural rigidities in both developing and advanced economies (Aghion, Boustan, Hoxby, & Vandenbussche, 2009; Banerjee & Duflo, 2005; Buera & Shin, 2013; Dollar & Wei, 2007; Gopinath et al., 2017; Linarello, Petrella, & Sette, 2019; Young, 2003).

[6] Factor income shares measure the percentage change in output from a 1% change in the respective input, holding the other constant; see Hall and Jones (1999) and Caselli (2005).

[7] This approach is standard in productivity analysis; see Bartelsman et al. (2013), Rogerson and Restuccia (2004), and Bils

The parameter α_s assigns the relative weight of capital and labour when constructing TFPQ, TFPR, MRPC, and MRPL. In doing so, it determines how distortions in each factor market drive the dispersion of TFPR.[8]

Misallocation Measurement. Let TFPR_{si} denote the revenue productivity of firm i in sector s, and $\overline{\mathrm{TFPR}}_s$ the sectoral average. In the efficient benchmark, $\mathrm{TFPR}_{si} = \overline{\mathrm{TFPR}}_s$ for all i, implying equalized MRPs within sectors. Firms with $\mathrm{TFPR}_{si} > \overline{\mathrm{TFPR}}_s$ are under-allocated (should receive more inputs), whereas those with $\mathrm{TFPR}_{si} < \overline{\mathrm{TFPR}}_s$ are over-allocated.

Following Calligaris et al. (2018), aggregate misallocation is proxied by the value-added–weighted variance of TFPR within sectors:

$$\mathrm{Var}(\mathrm{TFPR}) = \sum_{s=1}^{S} \frac{VA_s}{VA} \sum_{i=1}^{N_s} \frac{VA_{si}}{VA_s} \left(\mathrm{TFPR}_{si} - \overline{\mathrm{TFPR}}_s\right)^2, \tag{9}$$

where VA_{si} is firm VA, VA_s sector VA, and VA the aggregate total. Double weighting ensures that dispersion reflects welfare-relevant productivity implications rather than mere statistical spread.

In the Hsieh and Klenow (2009) framework and in the work from Calligaris et al. (2018), assuming a CES aggregator with substitution elasticity σ, sectoral TFP is inversely related to the variance of $\ln \mathrm{TFPR}$:

$$\ln TFP_s = \frac{1}{\sigma - 1} \ln\left(\sum_i A_{si}^{\sigma-1}\right) - \frac{\sigma}{2} \mathrm{Var}\left(\ln \mathrm{TFPR}_{si}\right). \tag{10}$$

A larger dispersion implies greater allocative inefficiency and lower aggregate productivity. The economy-wide TFP loss relative to the frictionless benchmark can be written as follows:

$$\frac{Y}{Y^*} = \prod_{s=1}^{S} \left[\sum_{i=1}^{N_s} \left(\frac{A_{si}}{A_s^*} \cdot \frac{\overline{\mathrm{TFPR}}_s}{\mathrm{TFPR}_{si}}\right)^{\sigma-1}\right]^{\frac{\theta_s}{\sigma-1}}, \tag{11}$$

where θ_s is the sector's value-added share (Calligaris et al., 2018; Hsieh & Klenow, 2009). The sectoral dimension highlights structural differences between industries and reveals how sector-specific distortions evolve over time, particularly in response to major economic disruptions such as the COVID-19 shock.

2.3 Olley & Pakes (1996)

To assess how firm heterogeneity and reallocation dynamics shape aggregate productivity, this study builds on the tradition of decomposition of Olley and Pakes (1996), further developed by Foster, Haltiwanger, and Krizan (2001), Melitz and Polanec (2015), and Altomonte and Di Mauro (2022). These approaches distinguish static, level-based decompositions from dynamic, change-based decompositions, thereby separating productivity into within-firm improvements, redistribution of resources between incumbent firms, and turnover effects from entry and exit.

Static decomposition. In the Olley and Pakes (1996) framework, aggregate productivity at time t can be

et al. (2018).

[8] Mis-specified factor shares bias productivity and distortion measures, underscoring the need to align empirical inputs with the theoretical framework (Gopinath et al., 2017).

expressed as:

$$\underbrace{P_t}_{\text{Aggregate Productivity}} = \underbrace{\bar{p}_t}_{\text{Within (mean productivity)}} + \underbrace{\sum_{i=1}^{N_t}(s_{it} - \bar{s}_t)(p_{it} - \bar{p}_t)}_{\text{Between (Olley and Pakes (1996)-gap / allocative efficiency)}} \quad , \tag{12}$$

where p_{it} denotes the productivity of the firm i, s_{it} its share of production, $\bar{p}_t$ the unweighted mean productivity, and $\bar{s}_t = 1/N_t$. The second term, known as the Olley and Pakes (1996)-gap, captures the covariance between productivity and market share. A positive Olley and Pakes (1996)-gap indicates that more productive firms command larger market shares, consistent with efficient allocation, while a negative or small Olley and Pakes (1996)-gap signals potential misallocation (Bartelsman et al., 2013; Foster et al., 2001; Olley & Pakes, 1996).

Dynamic extensions. Building on Melitz and Polanec (2015) and Foster et al. (2001), changes in aggregate productivity can be decomposed into components within-firm and between-firm terms for incumbents, as well as turnover effects from entry and exit. This dynamic specification highlights how reallocation and firm demographics contribute to aggregate productivity growth, particularly during periods of structural change such as the COVID-19 shock.

Focus on static decomposition. This study focuses on static Olley and Pakes (1996)-decomposition, which is well suited to measuring allocative efficiency at a given time point. The static approach allows for a detailed analysis of the dispersion and allocation of resources within the sector for each year, without requiring firm-level panel continuity or complex tracking of entry and exit. This enables robust cross-sectional comparisons and aligns with the primary aim of quantifying the extent of misallocation in the German manufacturing sector over the sample period.

Unlike the dispersion-based framework of Hsieh and Klenow (2009), which focuses on input distortions, the Olley and Pakes (1996)-decomposition emphasizes reallocation patterns within the firm distribution. As allocation can also be shaped by market power, this study complements the Olley and Pakes (1996) approach with markup-based indicators. Semi-parametric proxies (e.g., Lerner index) provide first insights, while parametric estimators enable a joint analysis of productivity, distortions, and pricing power (De Loecker & Warzynski, 2012; Dobbelaere & Mairesse, 2013).

2.4 Raval (2023)

To complement the analysis of misallocation, this study applies the flexible markup estimation framework developed by Raval (2023). This approach extends earlier work and provides a robust estimator under minimal assumptions, circumventing the need for physical quantity data, which is typically unavailable in European firm-level datasets (see also Bigio and La'O (2020), Bento and Restuccia (2017)).

The method of Raval (2023) is grounded in a Cobb–Douglas production function with constant returns to scale (CRS), implying that the sum of all factor elasticities equals one:

$$\sum_{X \in \{L,M\}} \beta^X = 1. \tag{13}$$

Raval (2023) further assumes constant output elasticities across firms within a sector and cost minimization, such that the first-order condition for input X equates its MRP to its marginal cost:

$$p_{it}^X = \mu_{it}^X \cdot \beta^X \cdot \frac{P_{it}Q_{it}}{X_{it}}, \tag{14}$$

where $p_{it}^X X_{it}$ denotes nominal expenditure on input X, $P_{it}Q_{it}$ is firm revenue, and μ_{it}^X is the input-specific markup.

Under these assumptions, the markup for factor X can be expressed as:

$$\mu_{it}^{X} = \frac{\beta^{X}}{s_{it}^{X}}, \tag{15}$$

where the revenue cost share s_{it}^{X} is given by:

$$s_{it}^{X} = \frac{p_{it}^{X} X_{it}}{P_{it} Q_{it}}. \tag{16}$$

In the CRS case, the output elasticity β^{X} can be recovered from the average input expenditure shares without requiring physical quantities. In the present application, markups are calculated for labour (L) and materials (M) (Raval, 2023).

The markup estimation by Raval (2023) offers three main advantages for my study. First, it enables factor-specific markup estimation for labour and materials using only financial data. Second, it complements the input-based measures of allocative efficiency derived from the dispersion of productivity in Hsieh and Klenow (2009) and the Olley and Pakes (1996)-decomposition with an output-based perspective. Third, it allows a direct test of allocative efficiency, which, in this setting, requires the equalization of factor markups within sectors.

From a theoretical perspective, efficient allocation requires that all input-specific markups are equal within narrowly defined sectors, regardless of the type of input:

$$\mu_{it}^{L} = \mu_{it}^{M}. \tag{17}$$

This condition implies that, in an efficient market, the MRP of each input is proportional to its marginal cost, and no input is systematically over or underutilized relative to others. Tracking these markups over time offers direct insight into the persistence and nature of input-specific distortions under changing economic conditions (De Loecker, Goldberg, Khandelwal, & Pavcnik, 2016; Raval, 2023).

Although the Raval (2023) approach estimates input-specific markups under flexible output elasticities, the existing literature has not explored the direct link between these markups and firm-level allocative efficiency. This study provides a interlinkage between the Hsieh and Klenow (2009) framework and the estimation of Raval (2023) by explicitly modeling the relationship between TFPR, TFP, and lagged input-specific markups, as also seen in Bertelsmann Stiftung (2023). This allows testing whether deviations from competitive benchmark markups in labour and materials markets are systematically associated with higher or lower allocative efficiency at the firm-level. Theoretically, under perfect competition and absence of distortions, input markups should be equal across inputs and uncorrelated with TFPR; significant deviations point to market imperfections with potential implications for aggregate productivity (Raval, 2023).

3. Data Description

I analyze capital and labour misallocation using a new firm-level dataset for German manufacturing firms from 2014 to 2022, constructed in cooperation with the Deutsche Bundesbank and harmonized with VGR sectoral aggregates. Restricted access to microdata enables precise identification of input distortions and productivity patterns, with transparent sample preparation ensuring empirical reliability and policy relevance (see main findings in Box A).

3.1 Firm-level Data

The data set description is based on the Deutsche Bundesbank Report (Becker, Biewen, Hüwel, & Schultz, 2024). Since the JANIS database is a confidential source of microdata that is not publicly accessible, providing a clear and precise description of its structure, variables, and preparation steps is crucial for the interpretability and credibility of this thesis. This section therefore outlines the characteristics of the underlying firm-level data, its coverage, and the procedures applied to construct the analytical sample. The core data source is the JANIS database (Research Data and Service Centre of the Deutsche Bundesbank, 2023) [9], provided by the RDSC of the Deutsche Bundesbank, the data report is from 2024, updated yearly. JANIS contains standardized annual financial statements of German non-financial corporations from 1997 to 2023 (with 2023 data still subject to revision). For my analysis, I used a raw version comprising more than 2.1 million firm-year observations and around 180 standardized accounting variables, encoded using alphanumeric labels.

The data set contains anonymized company identifiers (JANIS-ID) and includes employment information based on headcount. Since employment is reported voluntarily, the data exhibit substantial missingness and ambiguity regarding whether firms report full-time or equivalent full-time staff. Values may refer to annual averages or end-of-year figures. The financial statements come from two sources. First are balance sheets submitted to the Deutsche Bundesbank for credit assessments, and second, public filings with the Federal Gazette. All statements comply with German commercial accounting standards and undergo internal consistency checks (Becker et al., 2024).

The data set includes granular financial variables such as total assets, equity, sales, sales cost, various depreciation and tax components, export revenues, pension provisions (disclosed in notes), and R&D expenses measured in thousand euros. The firms in the sample span a range of legal forms, including GmbH (private limited liability company in Germany), AG (public stock corporation in Germany), partnerships, cooperatives, and sole proprietorships (Becker et al., 2024).[10]

Each observation represents a firm-year unit and includes structured data from the balance sheet, income statement, and asset disclosures, as well as metadata on industry classification (WZ 2008, based on NACE Rev. 2 (Statistisches Bundesamt (Destatis), 2008)), legal form, accounting standard, and firm size measured by headcount. Sectoral aggregation follows the official mapping of the WZ 2008 sections, as shown in Figure 3.

[9] German acronym: *Jahresabschlüsse von Nichtbanken im Inland – Statistik*, translated as *Annual Financial Statements of Domestic Nonbanks – Statistics*.

[10] GmbH and AG are the most common corporate legal forms in Germany, roughly corresponding to private limited and public stock corporations, respectively.

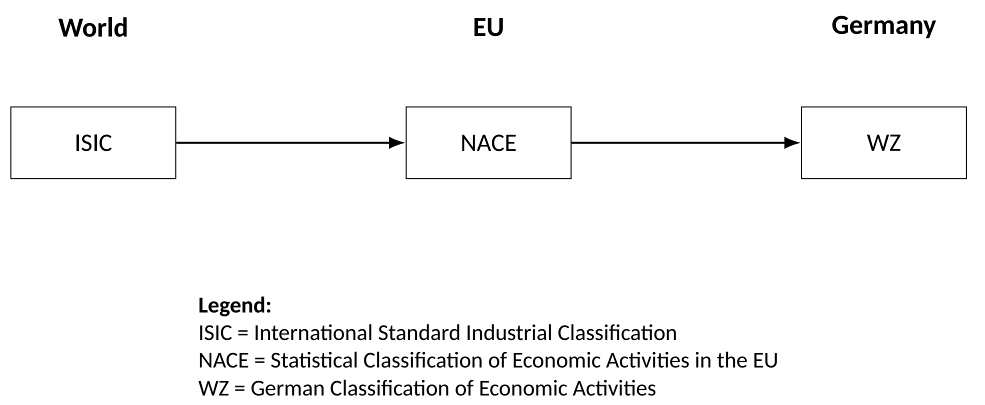


Figure 3: Mapping of Economic Classifications: ISIC, NACE, and WZ (World, EU, Germany). Adapted from Destatis (2008). Own illustration.

Compared to earlier firm-level data sets from the RDSC, JANIS offers better coverage of underrepresented sectors such as information & communication technology and hospitality, and includes a wider range of small and medium companies. Remaining limitations include short panel durations, missing observations, and zero values that may reflect non-reporting rather than actual firm behavior (Becker et al., 2024).

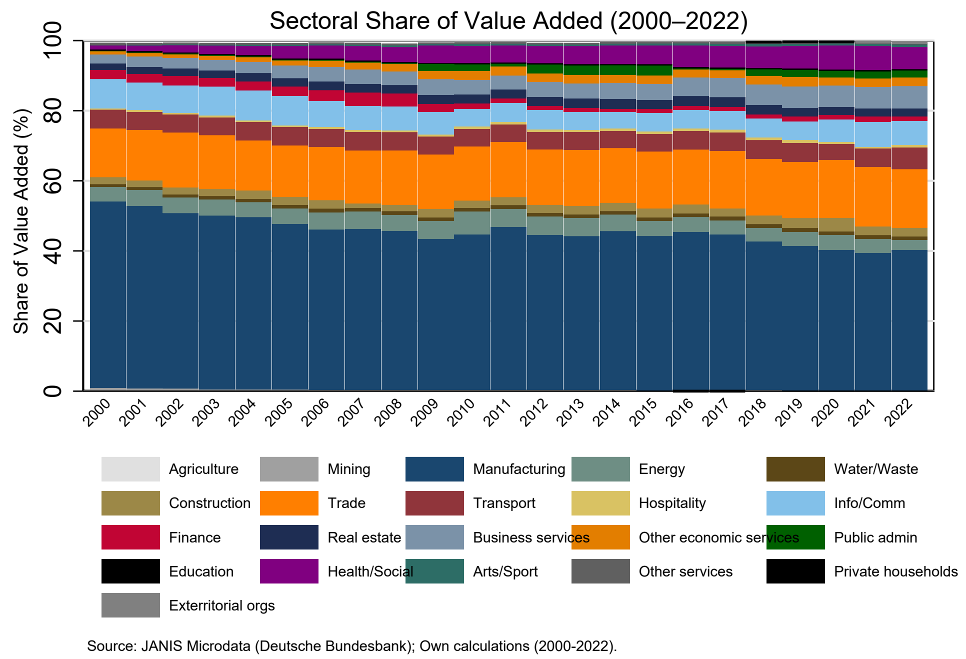


Figure 4: Sectoral Composition of Nominal VA in German Manufacturing (2000–2022). Source: JANIS microdata (Deutsche Bundesbank). Own calculations.

Figure 4 displays the annual value-added shares of 21 economic sectors based on firm-level data from the JANIS database (Research Data and Service Centre of the Deutsche Bundesbank, 2023). Manufacturing (highlighted in navy) remains the largest contributor about 40% throughout the period, although its relative share declines slightly over time. Given its economic weight and broad coverage of companies, the manufacturing sector is the primary focus of the analysis to ensure representativeness and analytical consistency.

The analytical sample is constructed through a multi-stage filtering process. In a first step, the sectoral scope is limited to manufacturing, defined by WZ 2008 codes 10 to 33. Code 19 (refined petroleum) is excluded due to extreme price volatility and resulting distortions (Eurostat, 2023; International Energy Agency, 2024).

Second, a capital ratio filter is applied to exclude firms with implausible capital-to-asset ratios based on sector-specific thresholds. Economically significant large firms are retained through a manual whitelist.

Third, firm identifiers are harmonized over time to ensure panel consistency. Additional firm characteristics are constructed, including legal form, accounting standard, firm age, and size class based on employment and revenue. The panel comprises companies with observed time span ranging from 1 to 27 years (see the average age of the firm over time in Appendix A in Figure A.17).

Finally, the core variables are constructed. The nominal VA is calculated as the difference between the sales and intermediate inputs based on the book values. All indicators — including fixed assets, investment, depreciation, and operating cash flow — are derived from the corresponding book values reported in the financial statements. Detailed internal comparisons with the commercial register for the year 2018 revealed that approximately 40% of the companies included in the study are covered by entries in the commercial register. Observations from 2023 are excluded due to incomplete reporting. The cleaned and constructed data set serves as the empirical basis for the misallocation estimation framework introduced in chapter 2.

3.2 National Accounts Data

The JANIS microdata cover only a subset of the German economy. To ensure representativeness, enable deflation, and benchmark firm-level results, I complement them with official macroeconomic aggregates.

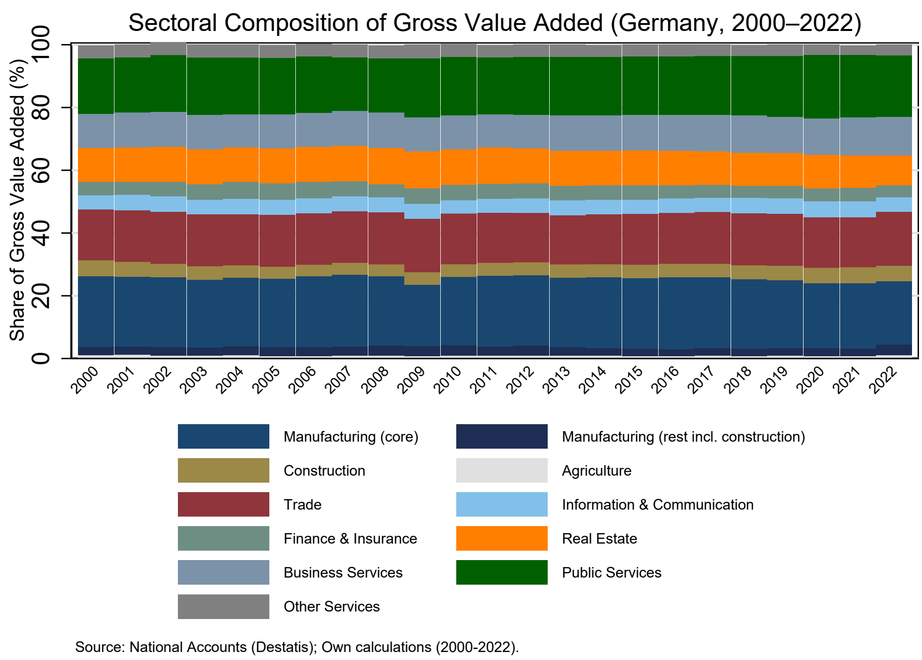


Figure 5: Sectoral Composition of GVA in Germany (2000–2022). Source: VGR (Destatis). Own calculations.

The VGR data from (Statistisches Bundesamt (Destatis), 2025) provide this comprehensive macroeconomic backbone, visualized in Figure 5 the VGR calculations are from May 2025. They cover all sectors of the German economy and allow for a consistent alignment between micro- and macro-level information, which is essential for contextualizing the subsequent productivity decompositions.

Figure 5 presents the sectoral composition of gross VA (GVA) based on official statistical accounts (VGR), as reported in Table 2 and sourced from (Statistisches Bundesamt (Destatis), 2025) 2.2.1. The manufacturing sector - including Manufacturing (core), shown in navy, and Manufacturing (rest, including construction) in dark blue - accounts for approximately 20% of the total GVA. This constitutes the largest share among all sectors, underscoring both the significance and the credibility of focusing the analysis on the manufacturing sector.

Unlike the firm-level microdata used in the JANIS-based analysis, these macroeconomic aggregates cover the entire German economy. This broader sectoral coverage, which includes agriculture, manufacturing, services, and the public sector, provides a representative basis for deflation, sectoral aggregation, and the normalization of capital–labour income shares. This comprehensive scope stands in contrast to the JANIS microdata (Research Data and Service Centre of the Deutsche Bundesbank, 2023), which are limited to a sample of non-financial corporations and exhibit a stronger concentration in the manufacturing sectors. To align firm-level records with macroeconomic aggregates, each firm is assigned a harmonized sector identifier that maps WZ 2008 industries to aggregated CA–CM sectors. Some subsectors (e.g. CE and CF) are merged because of small sample groups (harmonized to NACE chracterictics - EU standards). These mappings are applied throughout the analysis for deflation, sectoral aggregation, and graphical representation (see Table 2).

Table 2: Aggregation of WZ 2008 Manufacturing Sectors Based on VGR Classification (CA–CM). Source: VGR (Destatis), aggregated from Destatis (2008), WZ 2008 to CA–CM mapping. Own compilation.

Code	NACE	WZ08 Ranges and Description
1	CA	Food, Beverages, Tobacco (10–12)
2	CB	Textiles, Apparel, Leather (13–15)
3	CC	Wood, Paper, Printing (16–18)
4	CD	Coke and Refined Petroleum (19)
5	CE+CF	Chemicals and Pharmaceuticals (20–21)
6	CG	Rubber, Plastics, Glass, Ceramics (22–23)
7	CH	Basic and Fabricated Metals (24–25)
8	CI	Electronics and Optics (26)
9	CJ	Electrical Equipment (27)
10	CK	Machinery and Equipment (28)
11	CL	Motor Vehicles and Other Transport (29–30)
12	CM	Furniture, Miscellaneous Manufacturing, Repair (31–33)

Source: Aggregation based on VGR classification ((Statistisches Bundesamt (Destatis), 2008), WZ 2008 to CA–CM mapping).

All nominal variables are deflated using sector-specific deflators derived from VGR data provided by Fachserie 18 (Destatis). Table 3 summarizes the VGR tables used to construct real and nominal series for VA, production, capital, investment, and labour costs.

GVA (3.2.1) and output (3.2.3) in nominal terms are used to construct sectoral aggregates, while their chain indices (3.2.2, 3.2.4) serve as deflators to obtain real values. Investment and capital stock series (e.g., 3.2.9.1, 3.2.10.1, 3.2.23.1) are used to derive real capital input and to construct sector-specific capital stock indicators. Labour input is based on compensation data (2.2.7) and hours worked (2.2.13, 2.2.11), allowing for the calculation of average labour costs and scaling to the total workforce. GDP data (2.1.1) are used to normalize returns and compute aggregate shares for capital and labour.

To convert nominal firm-level variables into real terms, sector-specific deflators are constructed using chain indices from the VGR. For a given variable X in sector s and year t, the deflator is computed as:

$$\text{Deflator}_{s,t}^{X} = \frac{X_{s,t}^{\text{nominal}}}{X_{s,t}^{\text{real (chain index)}}} \times 100 \tag{18}$$

All deflators are rebased to 2020 = 100 to ensure consistency between variables. These deflators are then matched to firm-level observations by industry (WZ 2008) and year.

Table 3: Overview of VGR Tables Used in the Analysis. Source: VGR (Destatis), compilation based on Destatis (technical series 18).

Table	Title (Own English Translation)
Gross Value Added (GVA) and Output	
3.2.1	Gross Value Added – Nominal
3.2.2	Gross Value Added – Chain Index
3.2.3	Gross Output – Nominal
3.2.4	Gross Output – Chain Index
Investment and Capital Stock	
3.2.9.1	Gross Fixed Capital Formation – Nominal
3.2.10.1	Gross Fixed Capital Formation – Chain Index
3.2.23.1	Gross Capital Stock – Nominal
3.2.25.1	Gross Capital Stock – Chain Index
3.1.3	Gross Capital Stock – Nominal (Overview)
2.1.17	Gross Capital Stock – Real Index
Labour and Compensation	
2.2.7	Compensation of Employees
2.2.13	Hours Worked – Employees
2.2.11	Hours Worked – Total Employment
Macro Aggregates and Returns	
2.1.1	Gross Domestic Product – Nominal and Index

Source: Compilation based on data from Statistisches Bundesamt (Destatis) (2025).

The integration of VGR data with JANIS microdata ensures that all firm-level measures are expressed in real, comparable terms, and aligned with official macroeconomic aggregates, providing a consistent foundation for the estimation of misallocation presented in chapter 2..

3.3 Analysis Sample

Data for 2013 are retained only to compute growth rates for the (Olley & Pakes, 1996)-decomposition and are otherwise excluded. Table 4 provides an overview of the number of observations and firms included in the final analysis sample.

Table 4: Firm Coverage in the Manufacturing Sector (NACE C), 2013–2022 and 2014–2022. Source: JANIS microdata (Deutsche Bundesbank) and VGR (Destatis). Own calculations.

Time Range	Unique Firms	Observations
2013–2022	**24.893**	**116.224**
2014–2022	**22.618**	**102.962**

As shown in Figure 6, the so-called 'submarine effect' becomes apparent, not every firm appears in every year, and the entire set of firms is never observed simultaneously. This panel imbalance reflects both the entry and exit dynamics, as well as incomplete reporting (Becker et al., 2024).

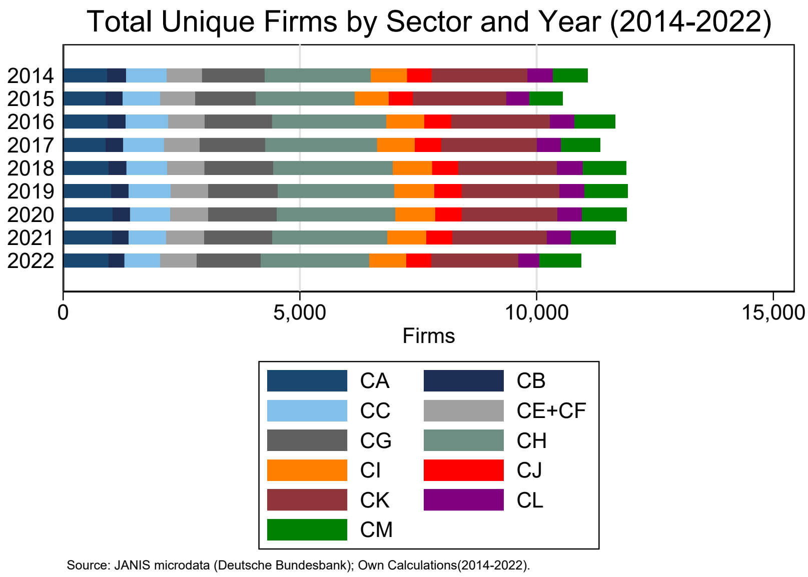


Figure 6: Number of Unique Firms by Sector and Year in German Manufacturing (2014–2022). Source: JANIS microdata (Deutsche Bundesbank) and VGR (Destatis). Own calculations.

The patterns observed in Figure 7 reveal a consistent decline in entry rates and a simultaneous increase in exit rates between the capital and labour quintiles over time. This trend aligns with the overall decrease in the number of active firms documented in Figure 6, suggesting a gradual erosion of the firm base during the observation period.

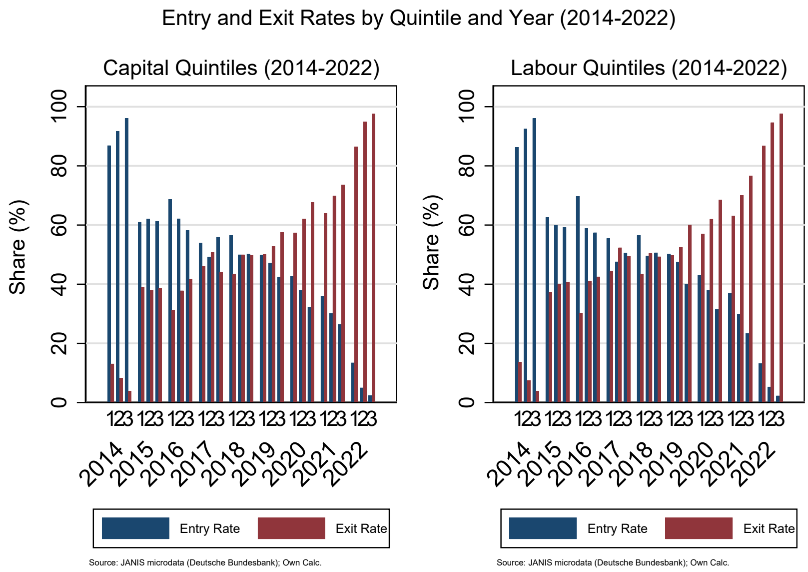


Figure 7: Entry and Exit Shares by Capital (K) and Labour (L) Quintiles by Sector and Year in German Manufacturing (2014–2022). Source: JANIS microdata (Deutsche Bundesbank) and VGR (Destatis). Own calculations.

Figure A.4 (Appendix A) shows the relative distribution of legal forms between firms in the JANIS microdata for the period 2014–2022. The vast majority of firms are registered as Limited liability companies (GmbH), followed by a smaller share of Limited partnerships with LLC as general partner (GmbH & Co. KG). All other legal forms, including public limited companies, cooperatives, and sole proprietorships, account for only a marginal share of the dataset. This distribution reflects the predominance of GmbHs in the German corporate landscape and highlights the dominance of hybrid legal structures for medium-sized enterprises.

The merged micro–macro dataset predominantly covers larger firms in terms of employment, capital, and VA. The following figures provide an overview of the firm structure along key dimensions that are used in the analysis later.

Before applying any outlier treatment, the firm distribution in the final matched sample is examined to show its qualitative structure. This motivates the choice of winsorization at the 1% and 99% levels, which reduces the influence of extreme values. I report alternative results using different time periods, winsorization thresholds, and value-added measures in Appendix C.

Figure 8 illustrates the distribution of employment across firm size classes (see also share of distribution of employment in Appendix A). The JANIS microdata exhibit particularly high coverage of medium-sized and large firms, which together account for the majority of total employment. This reflects both the reporting thresholds of the underlying administrative sources and structural characteristics of the German manufacturing sector, where labour input is concentrated in a relatively small number of firms.

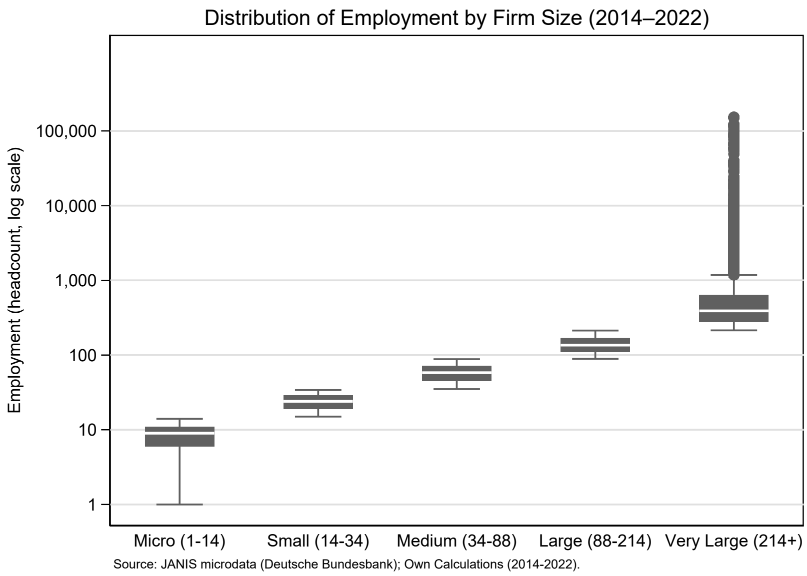


Figure 8: Distribution of Employment by Firm Size Class in German Manufacturing (2014–2022). Source: JANIS microdata (Deutsche Bundesbank) and VGR (Destatis). Own calculations.

This distribution pattern is relevant for the interpretation of allocative efficiency in empirical analysis. Since some large firms employ a disproportionate share of total labour, potential inefficiencies in the allocation of workers—e.g., reflected in unequal MRPs—may have a stronger aggregate impact than if employment were evenly distributed. In this sense, the dispersion of marginal returns across firms must be interpreted in light of their employment weights, a point that will be taken up in Section 5..

Figures 9 show the distribution of capital stock between the sizes of firms. Compared to employment, capital is even more concentrated: The largest firms hold more than 80% of the total capital stock in the sample. This pronounced skewness motivates the use of only three quantile groups in subsequent analyses (also underlined in the share of capital in Figure A.2 in Appendix A).

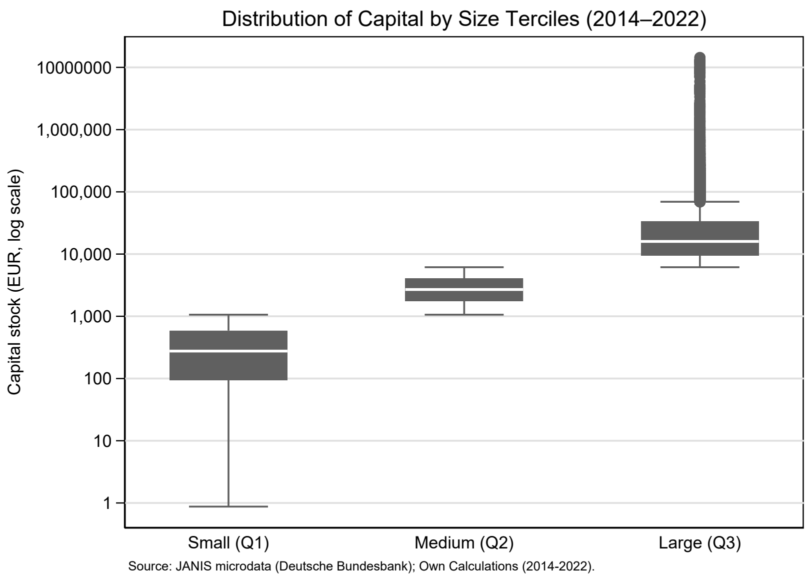


Figure 9: Distribution of Capital Stock by Tercile Groups in German Manufacturing (2014–2022). Source: JANIS microdata (Deutsche Bundesbank) and VGR (Destatis). Own calculations.

From the perspective of resource misallocation, this concentration implies that capital allocation distortions, if present, are likely to generate substantial aggregate TFP losses. In the Hsieh and Klenow (2009) framework, efficient capital allocation requires the equalization of firm-level MRPC weighted by capital input. Given the dominance of large firms in the total capital stock, deviations from this condition among these firms will be especially consequential, as discussed in Section 5..

Figures 10 show the distribution of VA between firms. Similar to capital, VA is highly concentrated among large firms: the top quantile group accounts for the vast majority of aggregate VA in each year.

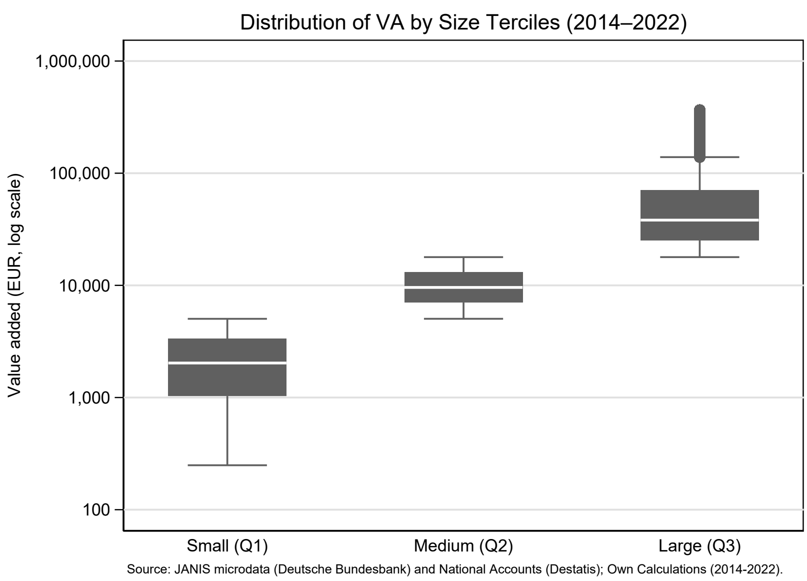


Figure 10: Distribution of VA by Tercile Groups in German Manufacturing (2014–2022). Source: JANIS microdata (Deutsche Bundesbank) and VGR (Destatis). Own calculations.

This concentration reflects the structural characteristics of the German manufacturing sector, in which a small number of firms contribute disproportionately to production (also highlighted in the share of VA in Figure A.3 in the Appendix A). From a measurement perspective, it reinforces the importance of accurately capturing firm-level variation among large producers, as their weight in aggregate TFP is substantial.

Sectoral composition and firm characteristics. The sample includes the full spectrum of German manufacturing (except petroleum, as stated earlier), ranging from low-tech sectors such as food processing to high-tech industries such as electronics and automotive. Sectoral coverage is particularly strong in capital and export-intensive branches, including machinery, chemicals, and transport equipment, reflecting both structural relevance and data availability in administrative sources.

Figure A.5 (Appendix A) shows that total employment in most manufacturing sectors decreased over time, especially after 2018. This reflects both firm exits and shrinking firm sizes, consistent with lower entry and higher exit rates. These trends may signal increasing frictions in labour reallocation or reduced firm dynamism. As employment becomes more concentrated in fewer firms, aggregate allocative inefficiencies may grow.

Figures A.6 and A.7 confirm that the sectors CL (Motor Vehicles), CK (Machineries) and CH (Metals) consistently employ the largest workforces, underscoring their central role in German manufacturing. Panel data reveal a general downward trend in employment in almost all sectors in recent years.

Figures A.8 and A.9 show similar patterns for capital stocks. The highest average capital is concentrated in CL (Motor Vehicles) and CE+CF (Chemicals and Pharmaceuticals), which also display the greatest capital intensity per firm.

Firm counts, shown in Figures A.10 and A.11, decreased in most sectors, especially in 2021-2022, reflecting the 'submarine effect' and trends in entry and exit rates.

Figure A.12 indicates that the ages of the firms range from 30 to 45 years, with the oldest firms in CA (Food, Beverages, Tobacco), CE + CF (Chemical and Pharmaceuticals) and CB (Textiles).

The duration of the panel (Figures A.13, A.14) is highly polarized: about 25% of the firms appear only once, while another 25% remain for the entire ten-year period.

Figures A.15 and A.16 reveal that CL (Motor Vehicles) and CE+CF (Chemicals and Pharmaceuticals) consistently lead in employment and capital per firm, while CB, CC, and CM represent sectors with much lower values.

Together, these patterns highlight the sectoral concentration, entry–exit dynamics, and panel structure that shape allocative efficiency outcomes in the German manufacturing sector.

Summary statistics. Table 5 and table 6 present descriptive statistics for key firm-level variables in the years 2014, 2020, and 2022. Variables include employment (L), capital stock (K), nominal VA (VA^{nom}) and real VA (VA^{real}), restricted to firms observed between 2014 and 2022.

Table 5: Descriptive Statistics of Firm-Level Variables in German Manufacturing by Year (2014, 2020, and 2022). Monetary values in €1,000, Employment in persons. Source: JANIS microdata (Deutsche Bundesbank) and VGR (Destatis). Own calculations.

Variable	**Obs.**	**Mean**	**Std. Dev.**
Year 2014			$(N = 11{,}079)$
Employment (L)	11 079	300.74	2 472.64
Capital stock (K)	11 079	18 843.77	201 164.00
Wage bill (W)	11 079	19 547.43	211 453.10
Intermediate inputs (M)	11 079	70 191.78	1 031 883.00
Nominal VA (VA^{nom})	11 079	25 668.67	50 336.03
Real VA (VA^{real})	11 079	42 002.84	411 438.10
Year 2020			$(N = 11{,}902)$
Employment (L)	11 902	265.68	1 793.13
Capital stock (K)	11 902	18 138.83	188 035.60
Wage bill (W)	11 902	18 652.67	171 038.00
Intermediate inputs (M)	11 902	57 424.95	770 818.20
Nominal VA (VA^{nom})	11 902	25 835.82	52 045.96
Real VA (VA^{real})	11 902	36 500.80	314 748.90
Year 2022			$(N = 10{,}940)$
Employment (L)	10 940	272.31	1 819.04
Capital stock (K)	10 940	18 519.17	201 008.20
Wage bill (W)	10 940	21 952.18	216 315.70
Intermediate inputs (M)	10 940	81 182.88	1 028 163.00
Nominal VA (VA^{nom})	10 940	29 368.41	57 125.01
Real VA (VA^{real})	10 940	43 273.46	417 001.00

Table 6: Descriptive Statistics for the Full Sample of Manufacturing Firms (2014–2022). Monetary values in €1,000; employment in persons. Source: JANIS microdata (Deutsche Bundesbank) and VGR (Destatis). Own calculations.

Variable	**Obs.**	**Mean**	**Std. Dev.**
Employment (L)	102 962	282.80	2 186.57
Capital stock (K)	102 962	19 010.32	207 807.60
Wage bill (W)	102 962	20 113.32	209 005.00
Intermediate inputs (M)	102 962	70 108.46	1 062 990.00
Nominal VA (VA^{nom})	102 962	26 744.03	53 046.93
Real VA (VA^{real})	102 962	41 334.39	406 987.20

Table 5 presents the mean and standard deviation of key variables at the firm-level: employment, capital stock, wage bill, intermediate inputs and nominal and real VA in the years 2014, 2020, and 2022.

Over the sample period, employment per firm decreased from an average of 301 in 2014 to 266 in 2020, before recovering slightly to 272 in 2022. This pattern is in line with the hypothesized prevalence of labour ditsortions (**H2**) and potentially reflects labour horarding and short-time work schemes (**RQ1,RQ2**). The capital stock remained relatively stable at the mean, fluctuating only modestly around €18,800 k, potentially not showing outliers that have a greater dispersion. The average wage bill decreased from about € 19, 500 k in 2014 to €18,700 k in 2020 and then increased to nearly €22,000 k in

2022. Intermediate inputs saw a substantial drop in 2020, falling from €70,200 k in 2014 to €57, 400 k, but increased sharply to more than € 81, 000 k in 2022. The nominal VA per firm remained stable between 2014 and 2020 (about € 25 700 k), with a noticeable increase to € 29 400 k in 2022. Real VA exhibited a similar pattern, decreasing in 2020 and then rising again in 2022.

Across the three years, the large standard deviations for each variable indicate a high degree of heterogeneity in firm size, input use, and productivity. For example, the distribution of employment, capital stock and VA is highly dispersed, with a small number of very large firms driving up both the mean and the variation.

Table 6 summarizes the entire sample period (2014–2022). The average manufacturing firm in Germany employed 283 people, held €19,010 k in capital stock, and generated €26,744 k in nominal VA, all with substantial spread around each mean.

These trends highlight substantial changes in firm activity, particularly around 2020, and emphasize the diverse scale and structure of firms in the sector. The observed variation and the dynamics across years provide an essential context for interpreting allocative efficiency and productivity dispersion in subsequent analysis.

The cleaned and deflated micro–macro dataset, summarized in Table 5, reveals marked changes in employment, capital intensity, and VA during the sample period, with clear disruptions around 2020. These descriptive patterns align with the hypothesized role of factor-specific distortions and crisis-induced shocks in shaping allocative efficiency. Based on this evidence, the dataset enables empirical implementation of the structural misallocation framework by Hsieh and Klenow (2009), as well as complementary approaches by Altomonte and Di Mauro (2022) and Raval (2023), to quantify and unravel the drivers of these dynamics. Taken together, the descriptive evidence highlights substantial variation in firm-level input structures, capital intensity, and VA over years, consistent with the hypothesized role of sectoral heterogeneity and crisis-induced distortions. These patterns provide the empirical background for the subsequent econometric analysis, where the cleaned and deflated micro-macro data set is used to quantify misallocation and allocative efficiency dynamics. A detailed summary of the analysis sample (2014–2022), including firm coverage, dynamics, size structure, and sectoral composition, is provided in the Appendix A in a result box A.

4. Methodology

This section presents the empirical implementation of the multi-method approach framework. A complete mapping of research questions and hypotheses to analytical frameworks is provided in Appendix B.1.

(Hsieh & Klenow, 2009): Misallocation Framework. The empirical strategy operationalizes the misallocation framework outlined in Section 2.2 to test the central hypothesis that persistent input distortions contribute substantially to productivity losses in the German manufacturing sector based on Calligaris et al. (2018); Hsieh and Klenow (2009). Capital input K_{si} is measured as the book value of fixed assets, while labour input L_{si} corresponds to headcount employment. The nominal VA VA_{si}^{nom} is calculated as sales minus intermediate inputs,

$$VA_{si}^{\text{nom}} = \text{sales}_{si} - \text{intermediate inputs}_{si},$$

and is deflated using sector-year gross VA deflators from the VGR to obtain real VA,

$$VA_{si}^{\text{real}} = \frac{VA_{si}^{\text{nom}}}{\text{Deflator}_{st}} \times 100,$$

thereby allowing for a distinction between revenue-based and quantity-based productivity measures (detailed implementation in Appendix B.2). Sector-specific capital elasticity α_s is inferred from the observed labour cost share as

$$\alpha_s = 1 - \frac{\text{wagebill}_{si}}{VA_{i,s}^{\text{nom}}},$$

where wagebill$_{si}$ includes wages, salaries, bonuses, and employer social contributions; the ratio is aggregated to the sector-year level to mitigate measurement error (see Appendix B.2).

Firm-level TFP is computed as the residual from a Cobb–Douglas production function,

$$TFP_{si} = \frac{VA_{si}}{K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}},$$

with VA_{si} defined either in nominal terms to obtain $TFPR$ or in real terms to obtain quantity-based productivity ($TFPQ$). In the misallocation framework of Hsieh and Klenow (2009) and Calligaris et al. (2018), the dispersion within the sector in TFPR is an indirect indicator of allocative inefficiency. TFPR is defined as

$$TFPR_{si} = \frac{VA_{si}^{\text{nom}}}{K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}},$$

and its dispersion is measured as Var$(\ln TFPR_{si})$, weighted by the firm's share in the nominal sectoral VA (weighting scheme in Appendix B.2).

To link TFPR to input-specific distortions, I also compute the MRPC and MRPL:

$$MRPC_{si} = \frac{\alpha_s \cdot VA_{si}^{\text{nom}}}{K_{si}}, \quad MRPL_{si} = \frac{(1-\alpha_s) \cdot VA_{si}^{\text{nom}}}{L_{si}},$$

which represent the returns to each factor in revenue terms. Under frictionless allocation, MRPC and MRPL are equalized between firms within a sector, implying constant TFPR. In practice, persistent dispersion in either MRPC or MRPL indicates factor-specific misallocation. In the analysis, the dispersion of $\ln MRPC$ and $\ln MRPL$ is calculated analogously to TFPR, and the three measures (TFPR, MRPC, MRPL) are compared over time and across sectors, including in the graphical analysis of Section 5..

Sectoral productivity A_s is obtained using a constant elasticity of substitution (CES) aggregator with elasticity of substitution $\sigma = 3$ (in line with Calligaris et al. (2018); Hsieh and Klenow (2009)) that incorporates distortions within the sector. A counterfactual benchmark A_s^* is calculated under the assumption that TFPR is equalized between all firms in the sector, that is, MRPs are identical within s. The total observed and counterfactual TFPs are then derived using fixed output weights θ_s, with the full CES derivations, sectoral benchmark definitions, and weighting procedures documented in the Appendix B.2.

Based on the theoretical framework and the descriptive patterns observed in the data, the Hsieh and Klenow (2009) implementation is expected to reveal persistently high within sector dispersion in TFPR, consistent with the presence of substantial and long-lasting input distortions in German manufacturing. Given the descriptive evidence of larger variation in capital-related returns, I expect MRPC dispersion to exceed MRPL dispersion, pointing to frictions in capital allocation as a more prominent source of misallocation. This pattern is anticipated to be particularly pronounced in capital-intensive sectors and during periods of economic stress, such as the 2008–2009 financial crisis and the 2020 COVID-19 shock, when allocative frictions tend to be amplified. Furthermore, counterfactual efficiency benchmarks A_s^* are expected to lie systematically above observed A_s across sectors, indicating a non-negligible efficiency gap and suggesting that reallocating resources toward more productive firms could yield substantial aggregate TFP gains.

(Olley & Pakes, 1996):Decomposition Strategy. To complement the dispersion-based misallocation analysis of Hsieh & Klenow (2009), I apply the decomposition framework introduced by Olley and Pakes (1996), which builds on Altomonte and Di Mauro (2022). This method separates aggregate productivity changes into a component within a firm, which captures the productivity growth of incumbent firms, and a component term of between-firm productivity, reflecting the reallocation of market shares between firms with heterogeneous productivity levels. Applying this approach to both LP and TFP allows me to assess whether the allocative patterns observed in the misallocation framework are consistent between different productivity concepts and measurement strategies.

The decomposition uses real VA per employee for LP,

$$LP_{it} = \frac{VA_{it}^{\text{real}}}{L_{it}},$$

and TFP as calculated in the Hsieh and Klenow (2009) implementation (Section 4.), based on real VA, real inputs, and user-cost adjusted capital. Both measures are expressed in logs and winsorized at the 1st and 99th percentiles within each sector-year. Firm-level employment shares s_{it} are used as weights, with average shares $\bar{s}_{it}$ taken over two consecutive years; as a robustness check, value-added shares are also applied (see Appendix B.3).

Aggregate productivity change is decomposed into the *within* component,

$$\sum_{i \in C} \Delta \ln P_{it} \cdot \bar{s}_{it},$$

where C is the set of continuing firms, and the *between* component,

$$\sum_{i \in C} \frac{1}{2}(\ln P_{it} + \ln P_{i,t-1}) \cdot \Delta s_{it},$$

where Δs_{it} is the change in a firm's employment share. A positive between-term indicates reallocation toward more productive firms. Aggregate productivity growth $\Delta \ln P_t^{\text{agg}}$ is checked to equal the sum of these two components up to rounding error. As an additional consistency check, the (Olley & Pakes, 1996)-gap is computed annually as the covariance between the deviations of market share and the deviations in productivity from the sectoral mean.

All components are calculated at the 2-digit WZ08 level (harmonized as showsn in Table 2) and then aggregated to manufacturing using sectoral employment weights. This decomposition provides a complementary perspective to the static HK framework: if the between-firm term is large and persistent, resource reallocation plays a substantial role in driving aggregate productivity growth; if instead the within-firm term dominates, technological improvements at the firm-level are the main driver.

By implementing the Altomonte and Di Mauro (2022) decomposition for both LP and TFP, I obtain a view of productivity growth that explicitly distinguishes between technological improvements within companies and efficiency gains from resource reallocation between companies. If the research hypothesis holds, the between-firm component should contribute significantly to aggregate productivity growth and its dynamics should align with the misallocation patterns detected in the Hsieh and Klenow (2009) analysis. Findings show that technological innovation among individual companies contributes more to overall productivity changes than shifts in how resources are distributed.

(Raval, 2023)): Input-Specific Markup Estimation.

To complement the allocation methodologies, I apply the factor-specific markup estimation framework proposed by Raval (2023). This approach allows for direct measurement of potential distortions in input markets by estimating separate markups for labour and material inputs. The empirical strategy is implemented in four steps (complete derivations, data definitions and robustness checks in the appendix B.4).

First, the nominal revenue cost shares are calculated for each input $X \in \{L, M\}$ as

$$\mu_{it}^X = \frac{\hat{\theta}_{it}^X}{s_{it}^X}, \quad X \in \{L, M\}$$

where Cost$_{it}^L$ denotes total labour compensation (wages plus employer social contributions) and Cost$_{it}^M$ intermediate inputs and services. Nominal sales are deflated using the sectoral production value deflator $\texttt{deflator\_prodval}_{st}$ to obtain real output Y_{it}.

Second, I estimate the firm-level output elasticities $\hat{\theta}_{it}^X$ using the production function:

$$\ln Y_{it} = \beta_0 + \beta_K \ln K_{it} + \beta_{it}^L \ln L_{it} + \beta_{it}^M \ln M_{it} + \omega_{it} + \varepsilon_{it}$$

where K_{it} is the real capital stock (constructed via the perpetual inventory method), L_{it} the headcount, and M_{it} the input of the real materials. The elasticities $\hat{\theta}_{it}^L$ and $\hat{\theta}_{it}^M$ are recovered from the estimated coefficients (Raval, 2023).

Third, input-specific markups are obtained as

$$\mu_{it}^X = \frac{\hat{\theta}_{it}^X}{s_{it}^X}, \quad X \in \{L, M\}$$

Under perfect competition and efficient allocation, markups should be equal across inputs within a sector, i.e. $\mu_{it}^L \approx \mu_{it}^M$. Persistent divergence between μ^L and μ^M signals factor-specific distortions.

Fourth, I examine the temporal co-movement of these markups and their relationship with productivity measures from (Hsieh & Klenow, 2009) implementation via fixed-effects regressions:

$$\ln(\mu_{it}^L) = \beta \ln(\mu_{it}^M) + \gamma_t + \delta_s + \alpha_i + \epsilon_{it}$$

$$\ln(Y_{it}) = \beta_L \ln(\mu_{i,t-1}^L) + \beta_M \ln(\mu_{i,t-1}^M) + \gamma_t + \delta_s + \alpha_i + \varepsilon_{it}$$

where Y_{it} is either TFPR$_{it}$ or TFPQ$_{it}$, γ_t are fixed effects for the year, fixed effects for the sector δ_s, and fixed effects for the firm α_i. Lagged markups mitigate the endogeneity bias; standard errors are clustered at the firm-level.

Based on the data description from chapter I hypothesize that material markups μ^M will on average exceed labour markups μ^L, reflecting greater pricing power and tighter constraints in intermediate input markets relative to labour markets. This divergence is expected to widen during periods of high TFPR dispersion, such as the COVID-19 pandemic, consistent with output distortions interacting with input-specific frictions. If the regression analysis reveals a positive association between lagged material markups and TFPR but a weaker or even negative association for labour markups, it would indicate that capital- and material-intensive firms have a comparative advantage in sustaining productivity under distorted conditions, whereas labour market frictions contribute less to allocative efficiency gains. Such a finding would support the view that Raval-based markup estimation offers a complementary dimension to the HK framework by distinguishing the sources of allocative inefficiency across input markets.

5. Results

Building upon the theoretical frameworks and the development of a consistent micro–macro data architecture, this section presents the empirical findings. For analytical clarity, the interpretation of results is systematically structured at the firm-level, sectoral, and aggregate levels of analysis.[11]

5.1 Misallocation Framework

As summarised in Box B.2, the misallocation analysis reveals persistent inefficiencies factor allocation, and thus in aggregate TFP, particularly after 2018.

5.1.1 Firm-Level Analysis.

In the Hsieh and Klenow (2009) framework, the dispersion of TFPR between firms serves as an indirect measure of misallocation: higher variance signals greater deviations from efficient allocation of inputs, and thus larger potential aggregate TFP gains from reallocation.

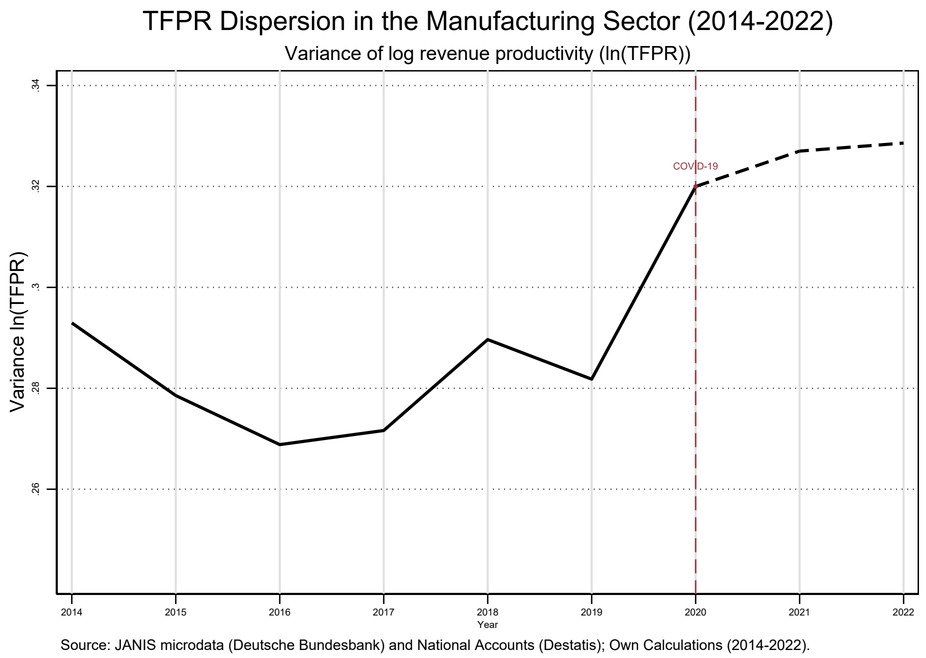


Figure 11: Evolution of TFPR Dispersion in German Manufacturing (2014–2022). Source: JANIS microdata (Deutsche Bundesbank) and VGR (Destatis). Own calculations.

Figure 11 shows the evolution of allocative efficiency in the German manufacturing sector between 2014 and 2022, measured as the annual variance of logarithmic transformation of TFPR between firms.[12] Calligaris et al. (2018) observe an earlier time period from 1995 (base year) to 2015, but even in this

[11] Appendix C.2 contains detailed robustness checks employing alternative winsorization thresholds (2%–98%, 5%–95%) to verify the stability of the results.

[12] TFPR dispersion is a standard proxy for misallocation in the Hsieh and Klenow (2009) framework, where a higher variance indicates a greater deviation from efficient allocation of factors. This sales-based variant follows Calligaris et al. (2018) and De Loecker and Goldberg (2014).

period they show reatively higher dispersion for the Italian manufacturing sector, peaking after the financial crisis between 0.35 and 0.4.

The results reveal a pronounced temporal variation in TFPR dispersion, addressing **RQ1** on the evolution of allocative efficiency over time. Between 2014 and 2016, the variance of the TFPR decreases slightly, suggesting a modest improvement in allocative efficiency. From 2016 to 2018, the dispersion increases, which could reflect cyclical investment patterns or sector-specific changes in capital availability David and Venkateswaran (2019) and supply chain disruptions in 2018 caused by Trump's first tariff wave on steel and aluminum Bown and Kolb (2018); Financial Times (2018). After a renewed contraction in 2019, the variance of TFPR increases sharply in 2020 with the onset of the COVID-19 pandemic, peaks in 2021, and only eases in 2022, yet remains above precrisis levels.

This persistence aligns with evidence from Dias et al. (2016) and David and Venkateswaran (2019) that large shocks can leave lasting misallocation scars, directly confirming **H1**: sectoral TFPR dispersion increased over the observation window, with a pronounced surge during the COVID-19 pandemic.

These dynamics match the macroeconomic channel in Baqaee and Farhi (2019), whereby distortions at the firm and sector levels amplify aggregate productivity losses. The pandemic in particular acted as aKeynesian supply shock “” (Guerrieri, Lorenzoni, Straub, & Werning, 2022), creating sector-specific constraints and demand changes that further increased the spread of TFPR (Dingel & Neiman, 2020; Fadinger, Schymik, et al., 2020). Appendix Figure C.20 confirms these analysis results using 2000 as the base year. The qualitative dynamics remain robust, showing the findings are not driven by the choice of benchmark year.

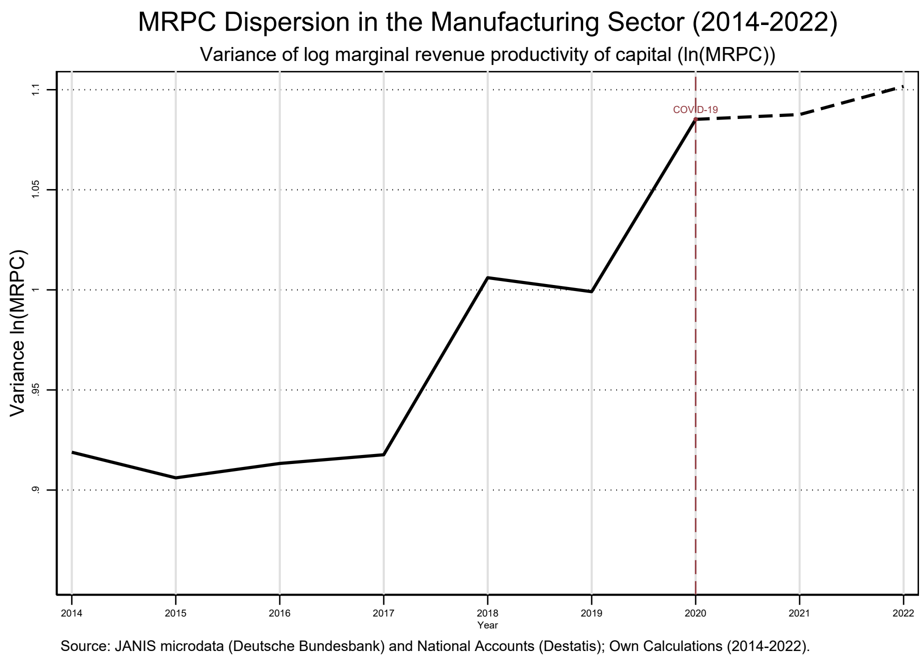


Figure 12: Dispersion of MRPC in German Manufacturing (2014–2022). Source: JANIS microdata (Deutsche Bundesbank) and VGR (Destatis). Own calculations.

The dispersion of MRPC across firms isolates capital-specific distortions: a higher variance indicates a greater wedge between actual and efficient capital allocation within sectors (Hsieh & Klenow, 2009).

Figure 12 shows the evolution of the dispersion of MRPC in the German manufacturing sector from 2014 to 2022. During 2014–2017, the dispersion remains low and stable, suggesting a comparatively even capital distribution. This coincides with the early phase of the unconventional monetary policy of the European Central Bank, when liquidity support and historically low interest rates improved financing conditions for many firms, including SMEs (Altavilla, Giannone, & Lenza, 2014; Altavilla, Pariès, & Nicoletti, 2019).

From 2018 onward, dispersion increases markedly, signalling a widening gap in capital allocation between more and less productive firms. Drivers likely include tightening credit standards in certain sectors, heterogeneous access to long-term financing, and shifts in banking relationships that favor incumbents over younger and potentially more productive entrants (Beck, 2020; Berlin & Mester, 2015; Meinen, Parrotta, Sala, & Yalcin, 2022).

This period also coincides with the first tariff wave imposed by the Trump administration, introducing 25% duties on steel and 10% on aluminium in March and June 2018. These measures disrupted global value chains and may have tightened financing conditions for firms reliant on imported intermediates, exacerbating capital market frictions (Bown & Kolb, 2018; Financial Times, 2018).

Dispersion peaks in 2020 with the onset of COVID-19, reflecting both reduced investment opportunities for some firms and an uneven distribution of liquidity support: well-connected firms or those in sectors less affected secured more favorable financing terms (Jimenez, Laeven, Martinez Miera, & Peydro, 2022; Laeven & Valencia, 2020).

Although MRPC dispersion declines slightly in 2022, it remains well above the 2014 baseline, indicating persistent postcrisis distortions in capital markets. This sustained elevation suggests that accommodative monetary policy alone is insufficient to restore allocative efficiency once sector-specific shocks and structural credit frictions take hold (Gopinath et al., 2017; Kalemli-Özcan, Laeven, & Moreno, 2022).

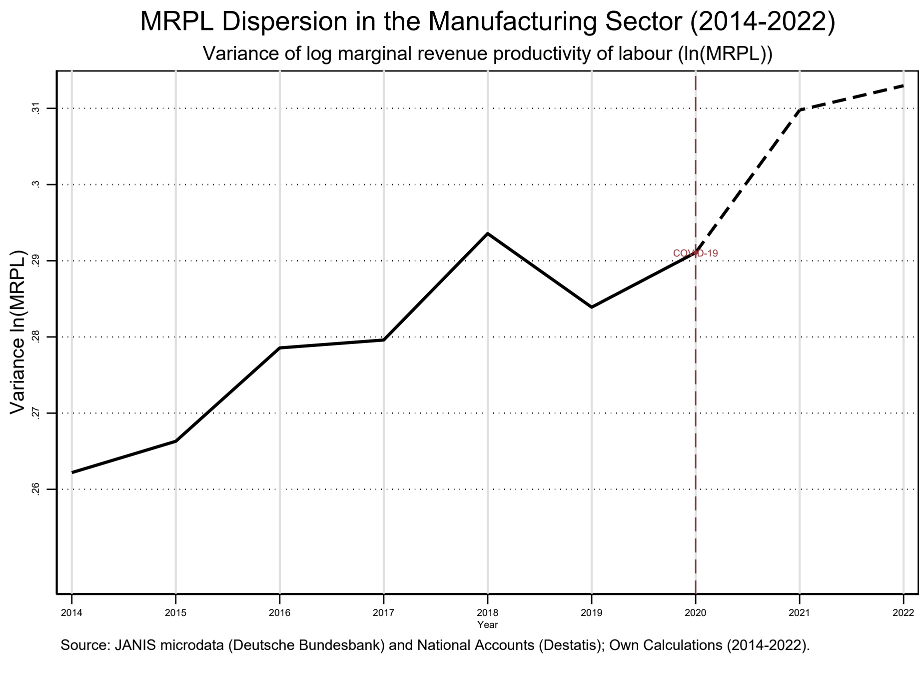


Figure 13: Dispersion of MRPL in German Manufacturing (2014–2022). Source: JANIS microdata (Deutsche Bundesbank) and VGR (Destatis). Own calculations.

Figure 13 shows the evolution of dispersion in MRPL in German manufacturing firms from 2014 to 2022. In contrast to capital misallocation, the increase in MRPL dispersion begins earlier, with a steady upward trajectory visible from the beginning onward. This trend continues until 2018, reaching a significantly higher level than in the base year 2014. After a brief contraction in 2019, the dispersion rises again in

2020, peaking in 2021 before stabilizing at a persistently elevated level in 2022. Appendix Figure C.22 confirms the robustness of these trends when using 2000 as the base year.

The earlier onset of an increase in labour misallocation compared to capital may be linked to structural characteristics of the German labour market and institutional frameworks that affect input flexibility. Measures such as short-time work schemes, continued wage payments during temporary work stoppages, and labour hoarding have been shown to reduce separations and preserve employment relationships during downturns (Arico & Stein, 2012; Boeri & Bruecker, 2014).

While effective at mitigating unemployment spikes, these policies can also lead to labour hoarding and slower reallocation of workers towards more productive firms, thereby increasing MRPL dispersion (Balleer, Gehrke, Lechthaler, & tian Merkl, 2016; Garnadt, von Rueden, & Thiel, 2021).

This effect may be amplified during periods of economic stress such as the COVID-19 pandemic, when state interventions cushioned labour demand shocks but simultaneously prolonged mismatches between labour allocation and firm productivity (Giupponi & Landais, 2022a).

When comparing factor-specific distortions, the MRPL dispersion remains lower than the MRPC dispersion (logged variances of approximately 0.28–0.31 vs. 0.90–1.10, respectively), suggesting that capital distortions are more severe, supporting **H2**: capital distortions contribute more to observed misallocation than labour distortions in scale, also seen in Calligaris et al. (2018) for the Italian manufacturing sector. However, the persistent post-2016 increase in the MRPL dispersion underscores that labour market frictions and state interventions can have enduring effects on allocative efficiency, even in highly regulated labour markets with strong employment protection.

5.1.2 Sectoral Analysis.

Figure 14 presents a sectoral decomposition of the TFPR dispersion in the German manufacturing sector (see the aggregation of the WZ 2008 manufacturing sectors based on the VGR classification (CA–CM) in Table 2), which provides deeper insight into heterogeneity in allocative efficiency across industries.

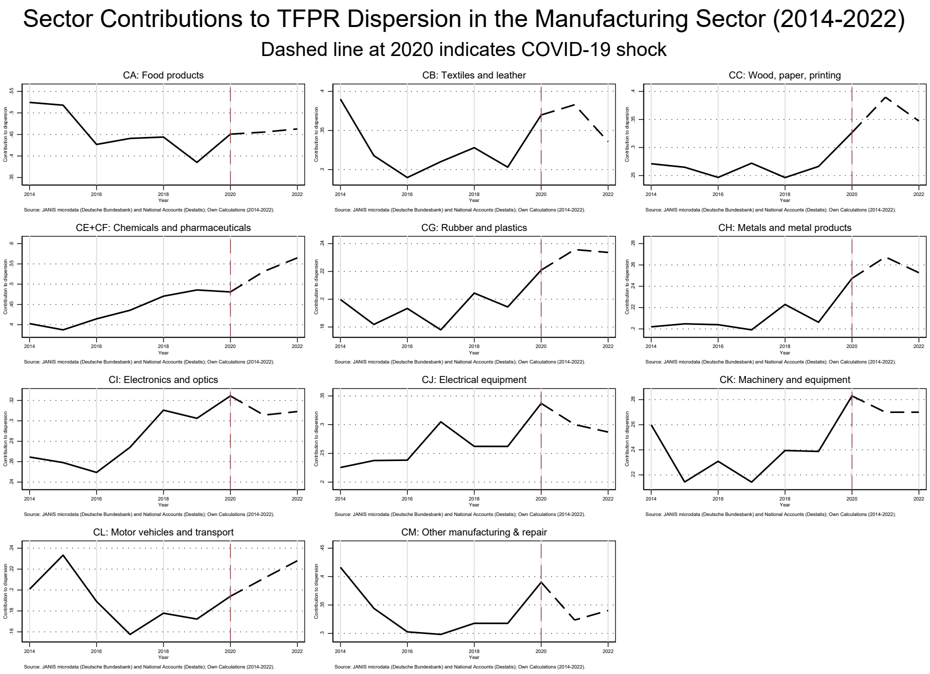


Figure 14: Sectoral Contributions to TFPR Dispersion in German Manufacturing (2014–2022). Source: JANIS microdata (Deutsche Bundesbank) and VGR (Destatis). Own calculations.

A clear structural break emerges in the pandemic year 2020, when many branches experienced a marked increase in the dispersion of MRPs, signalling heightened misallocation.

The industries most affected include chemicals and pharmaceuticals (CE–CF), rubber and plastics, glass and ceramics (CG), basic metals (CH), machinery (CK), and food processing (CA). Several of these sectors exhibited relatively low TFPR dispersion precrisis, suggesting that the increase was mainly driven by COVID-19-induced disruptions in supply chains and production processes. In contrast, industries such as basic metals (CH), fabricated metal products (CH), and mechanical engineering (CK) already showed elevated dispersion before 2020, which was further exacerbated during the pandemic (Bonadio, Huo, Levchenko, & Pandalai-Nayar, 2021; Evenett, 2020).

A distinct pattern emerges in the automotive sector (CL). Although motor vehicle manufacturing experienced a decline in the spread of TFPR in 2020 - possibly due to rapid adaptation and restructuring of demand - aerospace and rail transport manufacturing (CL) experienced a temporary increase in spread, which subsided largely in 2021. This is consistent with evidence on sectoral resilience and adaptability in manufacturing value chains. In contrast, the food and beverage industry (CA) maintained relatively stable allocative profiles, reflecting its essential sector status and limited exposure to global supply disruptions (Cirera et al., 2021; Javorcik, 2020).

Policy interventions critically shaped these outcomes. On the labour side, short-time work schemes and wage continuation policies mitigated employment losses but slowed the reallocation of workers towards more productive firms, in line with evidence on labour hoarding in downturns (Balleer et al., 2016; Giupponi & Landais, 2022a).

On the capital side, emergency aid, liquidity support, and investment subsidies maintained firm operations regardless of relative productivity, delaying market-based capital reallocation and contributing to rising MRPC dispersion in capital-intensive industries (Guerini, Nesta, Ragot, & Schiavo, 2020).

Interestingly, sectors with comparatively lower reliance on state aid, such as food manufacturing (CA), displayed more stable dispersion patterns, suggesting that while fiscal and credit policies play a stabilizing role in crises, they can also introduce persistent allocative inefficiencies by dampening competitive selection mechanisms (De Ridder, 2024).

In summary, these findings support **H3** by demonstrating pronounced heterogeneity in misallocation across sectors and firm sizes, while also directly addressing **RQ2** through the identification of key explanatory characteristics—namely, industry affiliation, pre-crisis TFPR dispersion, supply chain exposure, essential sector status, reliance on state aid, and sectoral adaptability—that shape the patterns of TFPR and MRPC dispersion, as well as their shifts during crisis periods.

5.1.3 Aggregate Analysis.

Figure 15 shifts the perspective from sectoral and input-specific patterns to the central aggregate outcome of the misallocation framework: the productivity gap between the aggregate TFP observed and its hypothetical efficient counterpart. Following Hsieh and Klenow (2009), this gap captures the extent to which capital and labour are not distributed in proportion to firm-level productivities, thus quantifying allocative inefficiency at the macrolevel.

The observed series reflects realized productivity given the prevailing distortions, while the efficient series estimates the counterfactual TFP attainable under frictionless reallocation of inputs. Both are expressed as cumulative changes relative to 2014, chosen as the benchmark year to ensure comparability of trends.

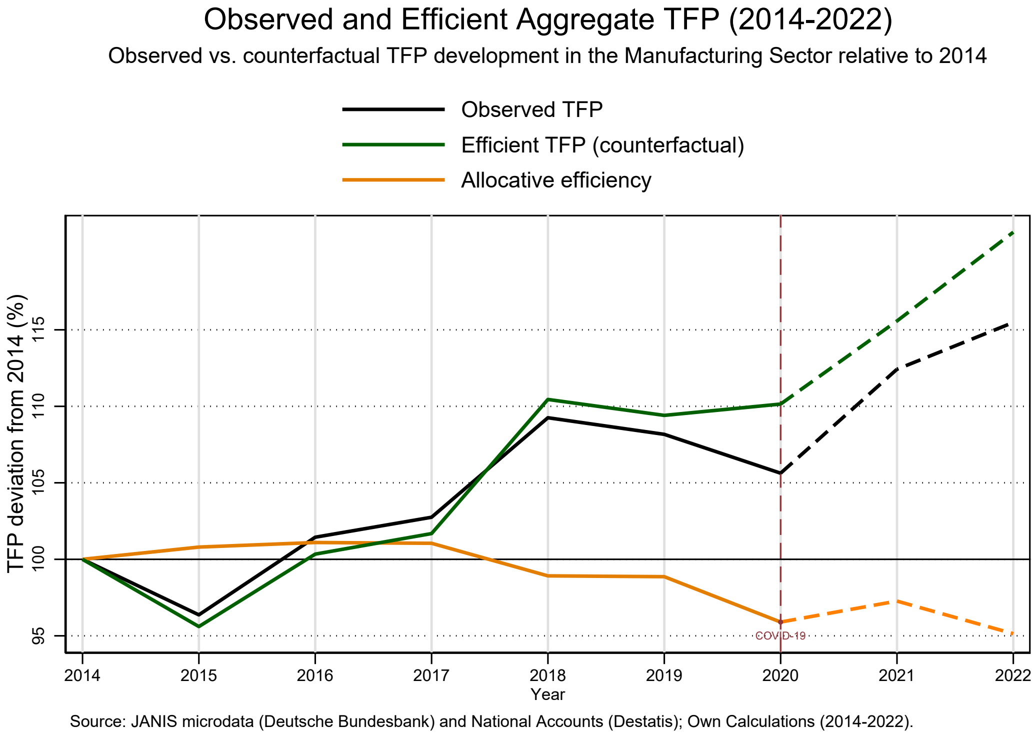


Figure 15: Observed vs. Efficient TFP and Allocative Losses in German Manufacturing (2014–2022, relative to 2014). Source: JANIS microdata (Deutsche Bundesbank) and VGR (Destatis). Own calculations.

The results in Figure 15 indicate three distinct phases. First, from 2014 to 2018, observed and efficient TFP moves broadly in parallel, with modest allocative losses of 1–2%. This period is consistent with findings from European manufacturing data showing relatively stable dispersion patterns in MPs before the COVID-19 pandemic (Calligaris et al., 2018).

Second, from 2018 to 2020, the efficiency gap widens as efficient TFP continues to grow while observed TFP stagnates. By 2020, efficient TFP is roughly 10% above the 2014 level, whereas observed TFP has increased by only about 5%, yielding an allocative loss of approximately 5%—the highest in the sample period. This magnitude is far below the potential TFP gains estimated by Hsieh and Klenow (2009) for China and India (30–60%) when benchmarked against the United States, reflecting the fact that Germany already operates at a comparatively high allocative efficiency level. It is, however, in line with more moderate gaps reported for advanced European economies.Calligaris et al. (2018) find efficiency losses of up to 23% in the Italian manufacturing sector when TFPR dispersion is equalized. Their observation window spans from 1995 to 2015, which may imply an even greater missed potential given the long period covered, with different crises, like the financial crisis peaking the dispersion, included (Calligaris et al., 2018).

Third, in 2021–2022, partial recovery is observed. Allocative losses narrow slightly in 2021, but remain elevated (around 4–5%) and increase again in 2022 as observed TFP stagnates while efficient TFP continues to grow. These persistent gaps echo concerns from the post-pandemic literature that crisis-induced interventions—while stabilising output and employment—may prolong inefficiencies by slowing the exit of unproductive firms and dampening factor reallocation (De Ridder, 2024; Guerini et al., 2020).

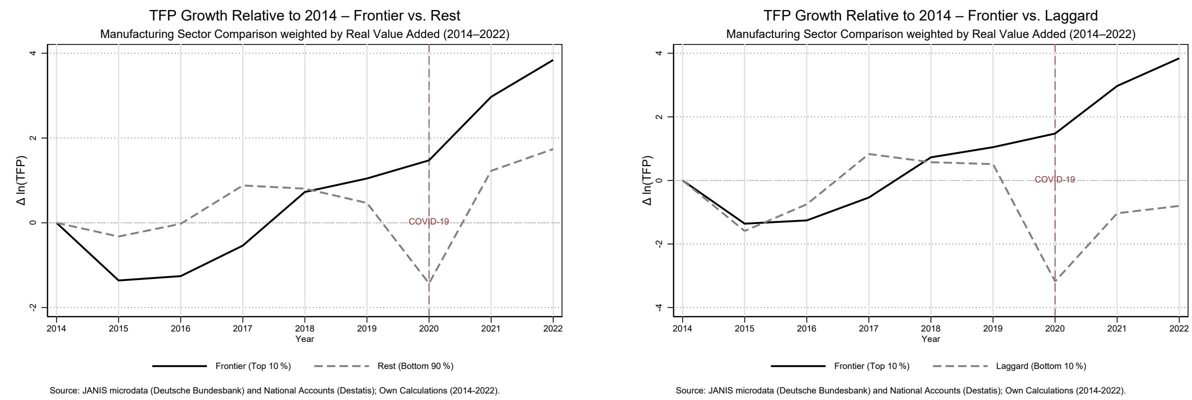
Importantly, this widening efficiency gap does not imply an absolute fall in productivity—both observed and efficient TFP rise over the sample period. Rather, it reflects a relative underperformance compared to the efficient benchmark. In other words, had the allocation efficiency of 2014 been maintained throughout the period, observed aggregate TFP would likely have followed a higher trajectory, more closely aligned with the efficient series. The estimated 5% gap in 2020 therefore represents foregone productivity gains relative to this counterfactual path—a loss that compounds over time and leaves the economy persistently below its potential (Bartelsman et al., 2013; Rogerson & Restuccia, 2004).

While a 5% efficiency gap is economically meaningful in a high-income context, it is modest compared to the magnitudes reported in the original Hsieh and Klenow (2009) study, where potential TFP gains from frictionless reallocation reached 30–60% for China and India relative to the United States. This divergence is intuitive: in emerging economies, factor market distortions are larger and more persistent, creating greater scope for allocative efficiency gains. In contrast, German manufacturing operates in a relatively mature institutional environment with tighter productivity distributions, limiting the potential upside from perfect reallocation.

Relative to other advanced economies, the magnitude observed here is in line with cross-country evidence for Europe. In the sample from Calligaris et al. (2018), Italy exhibits higher misallocation and TFPR variance than Germany, reflecting structural rigidities and weaker firm dynamics.

In particular, the widening efficiency gap after 2018 signals a departure from pre-pandemic stability and a decreasing trend in allocation efficiency—directly answering **RQ1**: allocation efficiency in German manufacturing declined over time, especially during the COVID-19 pandemic.

Technology Heterogeneity. To complement the aggregate and sectoral results, this section examines whether productivity dynamics are driven by firm-level technological heterogeneity. I compute TFPQ and classify the firms as frontier (top decile), laggard (bottom decile), and the rest. This corresponds directly to the perspective of “global frontier vs. laggard” perspective in the recent productivity literature, which documents widening gaps and slower diffusion of best practices (Andrews et al., 2016; Syverson, 2011).



(a) Frontier vs. Rest (b) Frontier vs. Laggards

Figure 16: Frontier, Rest, and Laggard TFPQ Dynamics in German Manufacturing (2014–2022). Source: JANIS microdata (Deutsche Bundesbank) and VGR (Destatis). Own calculations.

Figure 16(a) shows that TFPQ growth in German manufacturing has been disproportionately driven by frontier firms, with a widening gap versus the rest after 2018, likely showing the winner-takes-it-all behaviour. This pattern is consistent with international evidence on an expanding frontier–laggard differential and frictions that slow the diffusion of managerial and technological improvements (Andrews et al., 2016; Bloom, Sadun, & Van Reenen, 2016; Comin & Mestieri, 2010). The robustness check in Appendix Figure C.23 confirms that the frontier advantage is not sensitive to the base year.

Figure 16(b) explicitly adds the laggards, while they show a similar pattern, they lag in scale even lower behind. Although there is tentative convergence before 2018, the gap widens markedly thereafter and peaks around the COVID shock. The deterioration among the laggards is mirrored in a higher dispersion of TFPR and a higher dispersion of MRPC / MRPL, indicating that the resources remained tied to low-productivity plants rather than reallocated to the frontier, which addresses **RQ2** concerning firm-level and sectoral characteristics explaining dispersion and evolving patterns over time (Decker, Haltiwanger, Jarmin, & Miranda, 2016; Foster et al., 2008).

Figure A.17 provides sectoral trends in the average age of German manufacturing firms from 2014 to 2022, based on the newly constructed data set. Several sectors, including chemicals & pharmaceuticals (CE+CF) and machinery (CK), show a clear increase in average firm age, while sectors such as electronics (CI) and transport equipment (CL) maintain a relatively younger profile over time.

These patterns support my empirical finding that younger cohorts, visible in sectors with a lower average firm age, are overrepresented among the productivity frontier and demonstrate faster postcrisis recovery. In contrast, sectors with older firms tend to show greater persistence in the laggard status, in line with the literature: younger plants adapt technologies more rapidly and respond more strongly to competitive pressures (Aghion, Blundell, Griffith, Howitt, & Prantl, 2009; Hsieh & Klenow, 2014). Older firms, as seen in sectors such as food (CA) and textiles (CB), typically have more rigid capital structures and face greater adjustment frictions, which, combined with financing constraints, slow their ability to deepen capital and respond to shocks (Asker, Collard-Wexler, & De Loecker, 2014; Gopinath et al., 2017). Figure A.17 therefore illustrates how sectoral differences in age structure can reinforce the observed frontier–laggard split.

These results additionally provide evidence for **H2**, as they illustrate persistent resource misallocation: rather than being reallocated to more productive frontier plants, resources remain concentrated among laggards, resulting in higher dispersion of TFPR and MRPC/MRPL. This not only underscores the importance of firm-level and sectoral characteristics in explaining observed dispersion patterns (as addressed in **RQ2**), but also highlights how shocks such as the pandemic can exacerbate these inefficiencies over time.

Taken together, the gains led by the frontier and the stagnation of the laggard suggest that the diffusion and reallocation of technology operated below the potential over 2018–2022. This is consistent with the aggregate TFP gap: Even as the best performers advanced, frictions in the tails (age, size, finance, and supply chain exposure) limited economy-wide catch-up, providing evidence for **H3** that misallocation displays strong heterogeneity across sectors, firm sizes, and ages, and that exogenous shocks exacerbate these existing inefficiencies. Without targeted reallocation and diffusion policies, such as improving managerial practices, easing financing bottlenecks for scalable entrants, and facilitating labour mobility, the productivity reserves documented here are unlikely to be fully realized (Andrews et al., 2016; Bloom et al., 2016; Syverson, 2011).

5.2 Decomposition Framework

To further unravel the mechanisms driving the aggregate productivity dynamics, I apply the decomposition framework introduced by Olley and Pakes (1996) and adopted by Altomonte and Di Mauro (2022). This approach separates changes in aggregate productivity into two sources: within-firm improvements and reallocation of resources across firms with different productivity levels. My goal is to assess how much of observed productivity growth arises from firm-level efficiency gains versus improved resource allocation. As summarized in Box B.3, the Olley and Pakes (1996)-decomposition shows that gains within the firm clearly dominate reallocation effects.

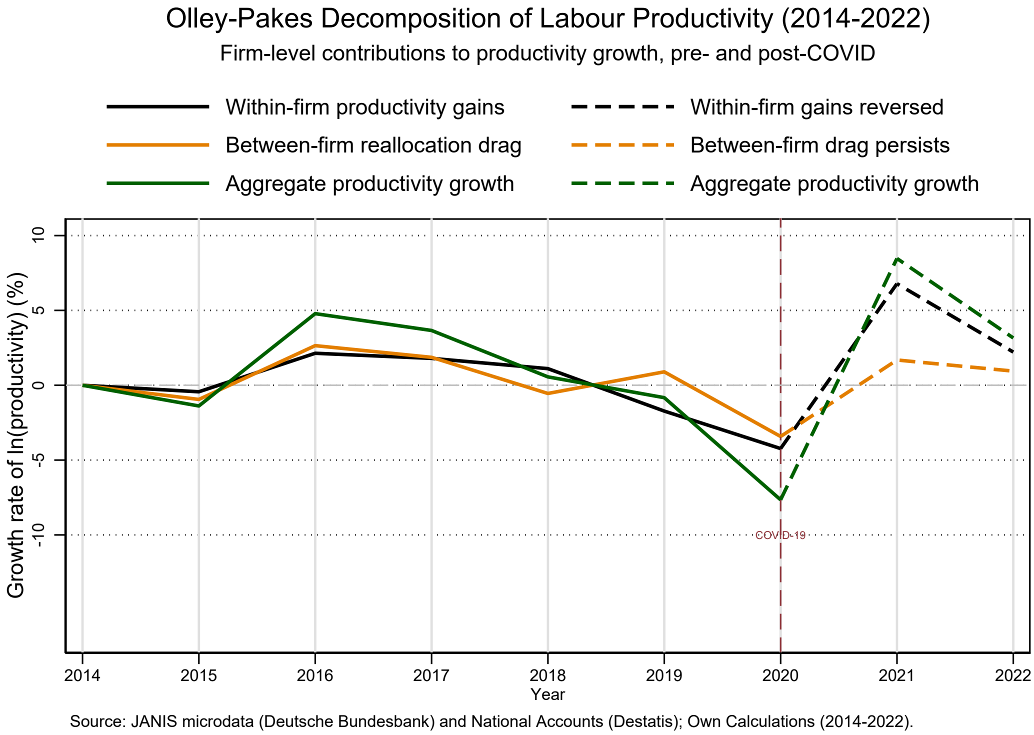


Figure 17: Decomposition of LP Growth in German Manufacturing: Within-Firm vs. Between-Firm Contributions (2014–2022). Source: JANIS microdata (Deutsche Bundesbank)and VGR (Destatis). Own calculations.

The decomposition of Olley and Pakes (1996) for LP (Figure 17) reveals three phases:

First (2014–2015), aggregate growth is high, with both the within-firm and between-firm components positive, although the between-term is smaller. This matches European evidence that reallocation plays a minor role in stable periods (Andrews et al., 2016; Syverson, 2011).

Second (2016-2018), all components are reduced and the difference between terms becomes negative, indicating that employment shares have shifted away from the most productive firms, consistent with documented structural frictions (Dias et al., 2016).

Third, the COVID-19 shock (2020) produces the steepest decline in the sample: both within-firm productivity and the between-term drop by around 5%. This signals simultaneous performance losses and limited cleaning reallocation (Barrero, Bloom, & Davis, 2020; Bartik et al., 2020). Pandemic stabilization policies—such as short-time work, wage subsidies, and liquidity guarantees—help explain this pattern. These interventions preserved incumbent employment matches but muted competitive selection, allowing low-productivity firms to retain market shares while high-productivity entrants faced growth barriers (Giupponi & Landais, 2022b).

The postpandemic rebound in 2021 was driven almost entirely by within-firm gains, with the between-term barely positive and flat in 2022. This “after-play” effect, where reallocation fails to amplify after support is withdrawn, reflects a COVID-19 paradox: Policy prevented short-term collapse but delayed structural adjustment.

The TFP decomposition (Figure 18) shows a similar weakness in the between-firm term, but with nuances.

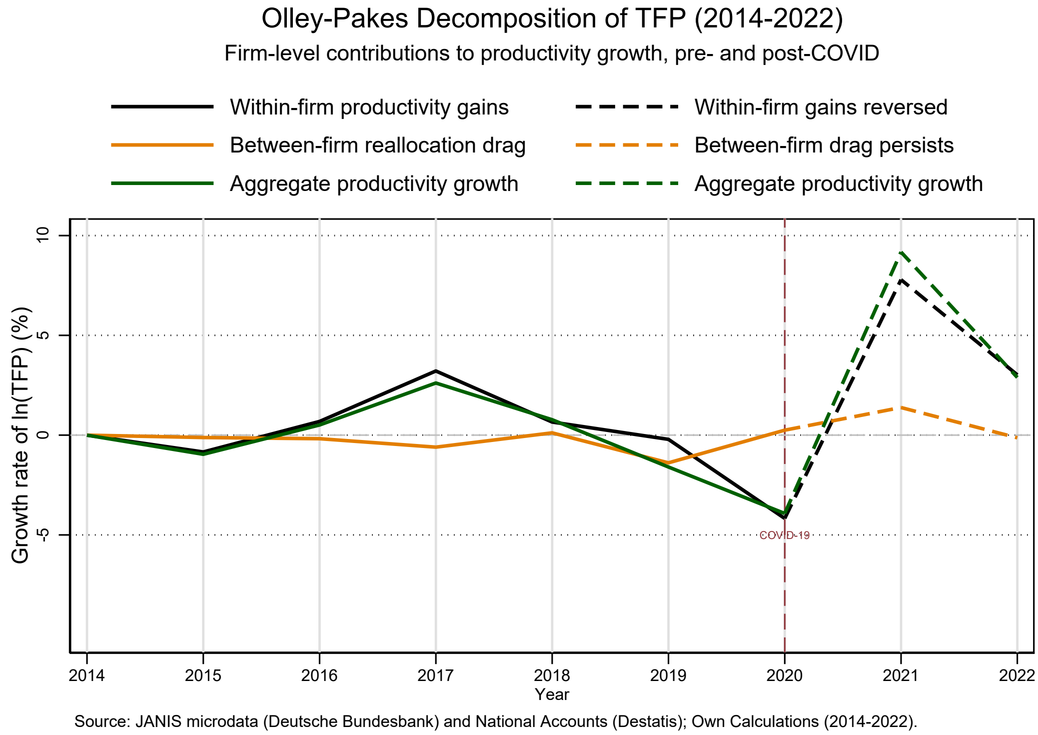


Figure 18: Decomposition of TFP Growth in German Manufacturing: Within-Firm vs. Between-Firm Contributions (2014–2022). Source: JANIS microdata (Deutsche Bundesbank) and VGR (Destatis). Own calculations.

From 2014 to 2019, the between-firm term in the Olley and Pakes (1996)-decomposition is mostly negative or close to zero, contributing little to aggregate TFP growth. In 2020, both aggregate and within-firm TFP collapse by about 5%, while the between-term remains near zero but trends upward through 2021 - contrasting with LP, where reallocation turned strongly negative. This indicates that the impact of the TFP pandemic operated mainly through uniform declines within the firm rather than spikes due to misallocation in that year. In particular, the effects of COVID-19 here reflect state subsidies to firms, which are not fully captured in the model due to missing profit data; thus, the leverage of reallocation arising from capital misallocation is muted.

In 2021, the between-term turn modestly positive (1–2%), and aggregate and within-firm productivity rebound strongly by approximately 10%. By 2022, the reallocation term returns to zero: mirroring LP, where the short-lived reallocation boost quickly fades and is not well detected within this model and its restrictions.

These results confirm **H4**: the Olley and Pakes (1996)-covariance term weakened during COVID-19, narrowing the Olley and Pakes (1996)-gap as incumbents retained market shares despite lower productivity, and high-productivity entrants faced limitations in expanding. Addressing **RQ3**, the evidence shows a structural break in the dynamics of reallocation during the pandemic: between-firm term contributions plummeted for LP or stayed neutral for TFP in 2020, recovered only briefly in 2021, and did not persist after the pandemic. The resilience of low-productivity incumbents underscores the effectiveness of state interventions in preserving capacity, but also their unintended consequence of delaying market-based reallocation.

The Olley and Pakes (1996) findings are aligned with the Hsieh & Klenow (2009) evidence in this thesis: TFPR and MRPC increased in 2020–2021, but the Olley and Pakes (1996)-covariance did not increase correspondingly. Both frameworks converge on the same conclusion—pandemic-era distortions heightened misallocation and muted competitive selection, highlighting the policy challenge of restoring both within-firm efficiency and the reallocation channel.

5.3 Evidence on Markups

This section adds a third analytical perspective by examining firm-level price–cost markups using the flexible estimation approach of Raval (2023). Key results are presented in Box B.4.

5.3.1 Descriptive Evidence.

Factor-specific markups in German manufacturing deviated and diverged substantially between 2014 and 2022, with this divergence most pronounced during the COVID-19 pandemic—answering **RQ4**, which asks whether factor-specific markups deviate and diverge in periods of disruption, and providing evidence for input-specific distortions.

Labour and material markups followed different cyclical paths, implying that disruptions affected factor markets asymmetrically. Labour markups were more volatile and sensitive to labour-market policies (e.g., short-time work), while material markups were more directly impacted by supply-chain shocks and cost pass-through. These deviations point to persistent input-specific frictions: labour hoarding, bargaining power asymmetries, and input bottlenecks, not captured by TFPR dispersion or Olley and Pakes (1996)-gap measures alone.

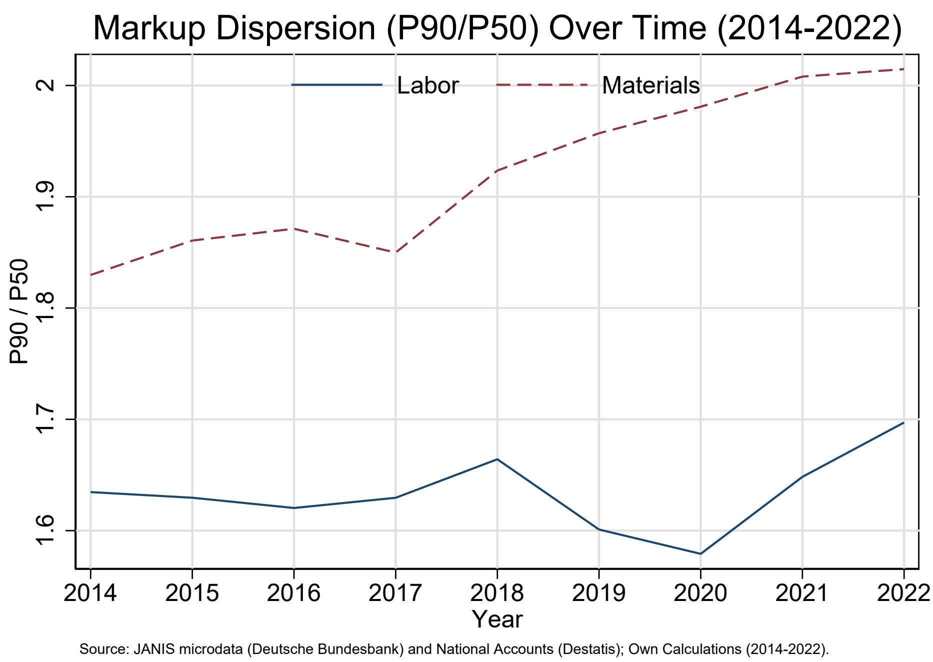


Figure 19: Markup Dispersion (90/50 Percentile Ratio) for Labour and Materials in German Manufacturing (2014–2022). Source: JANIS microdata (Deutsche Bundesbank) and VGR (Destatis). Own calculations.

Figure 19 confirms that labour and material markups diverged most strongly in 2020, as material markups surged and labour markups fell or stabilized. This divergence is consistent with input-specific distortion: pandemic-era supply shortages increased the MRP of materials, while extensive labour-market interventions muted wage and employment adjustments—confirming **H5** that input markups diverged most strongly during periods of disruption. The persistence of higher material-markup dispersion into 2021–2022, along with a rebound in labour-markup dispersion, suggests that both temporary shocks and structural rigidities contributed the widening of the input wedges.

From a perspective of misallocation, this mirrors the Hsieh and Klenow (2009) finding of a rising TFPR dispersion without a corresponding increase in reallocation, implying that competitive equalization of MPs remained incomplete during and after the pandemic.

Figure 19 shows that the dispersion levels are systematically higher for materials, ranging between approximately 1.8 and slightly above 2.0 than for labour, which fluctuates between 1.6 and 1.7. This persistent gap suggests that material-input wedges are more heterogeneous and less subject to competitive equalisation than labour wedges.

These findings reinforce **H2** by demonstrating that material-input wedges exhibit persistently greater heterogeneity compared to labour-input wedges, indicating that resources are not efficiently reallocated, and competitive pressures are less effective in equalizing markups across firms with respect to materials.

Over time, material-markup dispersion declined mildly until 2017, then rose steadily to a peak in 2021 before easing slightly in 2022. In contrast, labour-markup dispersion fell until 2016, rose briefly in 2018, then dropped sharply in 2020 before rebounding. The crisis year 2020 stands out: material dispersion surged while labour dispersion fell, consistent with heterogeneous market disruptions—supply-chain bottlenecks in materials input versus muted labour adjustment due to stabilisation policies (Balleer et al., 2016; Giupponi & Landais, 2022b).

From the Hsieh and Klenow (2009) perspective, elevated and widening dispersion signals greater misallocation, as MRPs deviate more strongly between firms within narrowly defined sectors. The asymmetric shock response in 2020 suggests that input-specific wedges $(\tau^M \neq \tau^L)$ shifted rapidly in opposite directions, potentially reflecting differences in adjustment costs, contract rigidity, and exposure to global shocks. According to the Olley and Pakes (1996) and Altomonte and Di Mauro (2022) decomposition frameworks, the pandemic shock corresponds primarily to changes within the firm in mark-ups, with limited evidence of reallocation between firms during the crisis years - consistent with the Olley and Pakes (1996)-gap patterns observed in this analysis.

5.3.2 Regression Results.

Correlation Between Labour and Material Markups. Before assessing the productivity implications of input markups (Table 9), it is essential to examine whether labour and material markups move together over time. Such co-movement would suggest the presence of common factor market distortions that could jointly affect allocative efficiency.

To quantify this relationship, I estimate the following specification:

$$\ln(\mu_{it}^L) = \beta \ln(\mu_{it}^M) + \gamma_t + \delta_s + \alpha_i + \epsilon_{it}, \tag{19}$$

where γ_t, δ_s, and α_i denote year, sector, and fixed effects of the firm, respectively. This corresponds closely to Equation (9) in Raval (2023), but is adapted to the German manufacturing context and my sales-based markup estimation framework.

Table 7 reports the results. The estimated elasticity of $\hat{\beta} = 0.558$ ($p < 0.01$) lies above the 0.4–0.5 range documented by Raval (2023) for US manufacturing, indicating a strong and statistically significant co-movement between labour and material markups in German manufacturing. The within-R^2 of 0.386 suggests that material markups and fixed effects explain a substantial share of the variation in labour markups.

Such a high degree of correlation implies that factor-specific distortions often evolve jointly rather than independently. This pattern is consistent with institutional and structural characteristics of the German economy, including coordinated wage bargaining Dustmann, Fitzenberger, Schönberg, and Spitz-Oener (2014); Jäger, Naidu, and Schoefer (2024), integrated supply chain relationships Carvalho, Nirei, Saito, and Tahbaz-Salehi (2020); Schmieder, von Wachter, and Heining (2023), and regulatory frameworks that shape labour and intermediate input markets (Conway, Janod, & Nicoletti, 2005). In the Hsieh and Klenow (2009) framework, such correlated distortions imply common wedges across factor markets, thereby amplifying aggregate TFP losses (e.g. Amiti, Itskhoki, & Konings, 2019; De Loecker & Goldberg, 2014).

Table 7: Relationship Between Labour and Material Markups in German Manufacturing Firms (2014–2022). Source: JANIS microdata (Deutsche Bundesbank) and VGR (Destatis). Own calculations.

	Dep. var.: $\ln(\text{Markup}_L)$
$\ln(\text{Markup}_M)$	0.558***
	(0.00582)
Year fixed effects	Yes
Industry fixed effects (2-digit)	Yes
Firm fixed effects	Yes
Observations	102,962
Number of firms	22,618
Within R^2	0.386

Notes: Fixed-effects (within) regression with firm-level panel data. Robust standard errors clustered at the firm-level in parentheses. All specifications include year and 2-digit industry dummies. *** $p < 0.01$.

In the context of **RQ4** and **H5**, this finding suggests that the pandemic shock and subsequent recovery reinforced multi-dimensional inefficiencies, rather than triggering purely input-specific adjustments. The persistence of this co-movement highlights that shocks such as the COVID-19 pandemic can simultaneously disrupt multiple input markets, amplifying allocative inefficiency as reflected in the dispersion patterns documented in Figure 19.

Time Trends in Input Markups. To analyse the temporal evolution of input-specific market power, I estimate fixed-effects regressions of the form:

$$\ln(\mu_{it}^X) = \gamma_t + \delta_s + \alpha_i + \epsilon_{it}, \quad X \in \{L, M\}, \tag{20}$$

where γ_t denotes fixed effects by year, δ_s controls sector heterogeneity by two digits, and α_i captures persistent firm-level heterogeneity. This specification follows Raval (2023), who emphasizes the importance of distinguishing markups by input type to uncover input-specific distortions in production.

Table 8 reveals three key patterns. First, labour markups were relatively stable before 2019 but rose sharply in 2020 ($\hat{\gamma}_{2020}^L = 0.032, p < 0.01$) due to wage rigidities, short-time work, and output contractions Giupponi and Landais (2022c); OECD (2021), before falling markedly in 2022 ($\hat{\gamma}_{2022}^L = -0.064, p < 0.01$). Second, material price increases increased steadily from 2015, reaching a peak in 2020 ($\hat{\gamma}_{2020}^M = 0.088, p < 0.01$)—almost three times the gain in the price of labour - driven by supply chain disruptions Carvalho et al. (2020); Schmieder et al. (2023), with only partial correction in 2022 ($\hat{\gamma}_{2022}^M = -0.031, p < 0.01$). Third, the larger amplitude for materials and the sharper post-peak decline for labour reflect differing adjustment mechanisms: coordinated wage bargaining versus globalized input sourcing.

From a misallocation perspective, the pandemic not only altered the level of input-specific markups but also increased their co-movement across inputs (see Table 7). This supports **RQ4** and **H5**, showing that during COVID-19, distortions in labour and material markets became more synchronised, amplifying their joint impact on allocative efficiency. Moreover, the sharper and more persistent increase in material mark-ups indicates that structural features -such as sectoral wage bargaining, coordinated supply chains, and regulatory frameworks - can prolong the effects of shocks, maintain mark-up differentials, and reinforce dispersion as a key misallocation channel in the Hsieh and Klenow (2009) framework, consistent also with **H2**.

Table 8: Time Trends in Labour and Material Input Markups in German Manufacturing Firms (2014–2022). Source: JANIS microdata (Deutsche Bundesbank) and VGR (Destatis). Own calculations.

	$\ln(\text{Markup}_L)$	$\ln(\text{Markup}_M)$
Year FE coefficients		
2015	-0.00785***	0.01194***
	(0.00259)	(0.00271)
2016	0.02299***	0.03395***
	(0.00284)	(0.00315)
2017	0.00764**	0.01505***
	(0.00301)	(0.00334)
2018	-0.01499***	0.01569***
	(0.00313)	(0.00354)
2019	0.00694**	0.03699***
	(0.00324)	(0.00369)
2020	0.03182***	0.08783***
	(0.00342)	(0.00385)
2021	-0.00297	0.02512***
	(0.00355)	(0.00401)
2022	-0.06441***	-0.03076***
	(0.00383)	(0.00436)
Within R^2	0.0168	0.0196

Notes: Coefficients are from fixed-effects panel regressions of log input markups on year and sector dummies. Parentheses indicate firm-level clustered standard errors. The base year is 2014. *** $p < 0.01$, ** $p < 0.05$.

Extension: Input Markups and Productivity. To explore whether factor-specific distortions systematically affect firm-level productivity, I extend the baseline Hsieh and Klenow (2009) specification by including lagged labour and material markups estimated following Raval (2023).

This approach allows for distinguishing the productivity effects of deviations from competitive benchmark markups at the input level. The one-year lag mitigates potential reverse causality, whereby contemporaneous productivity shocks could influence markup setting.

Table 9 reports the results for both $\ln TFP$ and $\ln TFPR$ as dependent variables. All regressions include fixed effects for the firm, year, and sector; standard errors are clustered at the firm-level.

The results indicate a statistically significant and economically meaningful relationship between the input mark-ups from the previous year and the current productivity. A 1% increase in the labour markup is associated with an estimated 0.035% rise in TFP and 0.032% in $TFPR$. In contrast, a 1% increase in material mark-up reduces TFP by 0.022% and $TFPR$ by 0.018%. These contrasting signs suggest that factor-specific market imperfections have asymmetric effects on productivity.

Table 9: Fixed-Effects Regressions of Productivity on Lagged Input Markups in German Manufacturing Firms (2014–2022). Source: JANIS microdata (Deutsche Bundesbank) and VGR (Destatis). Own calculations.

	(1) $\ln TFP$	(2) $\ln TFPR$
Lagged labour markup	0.0351***	0.0325***
	(0.00842)	(0.00830)
Lagged material markup	-0.0218**	-0.0184**
	(0.00854)	(0.00846)
Year FE	Yes	Yes
Sector FE (2-digit)	Yes	Yes
Firm FE	Yes	Yes
Observations	74,657	74,657
Number of firms	17,038	17,038
Within R^2	0.0224	0.0575

Notes: Coefficients are from fixed-effects panel regressions of productivity measures on lagged log input markups, controlling for year and 2-digit sector fixed effects. Parentheses indicate firm-level clustered standard errors. *** $p < 0.01$, ** $p < 0.05$.

The positive association between labour markups and productivity may reflect mechanisms such as efficiency wages, skill complementarity, or labour hoarding in downturns, consistent with Klette and Griliches (1996). In contrast, Bertelsmann Stiftung (2023) report negative effects for an earlier period (2007–2016), which may reflect differences in data coverage, sample composition, and, most importantly, the absence of the COVID-19 pandemic in their observation window.

The negative link for material markups supports the view that high intermediate input prices restrict the scale and efficiency of the downstream firm, in line with Aghion, Antonin, and Bunel (2021).

In summary, this chapter has documented persistent and crisis-driven patterns of misallocation and input-specific distortions in German manufacturing. The analyses reveal how factor market frictions, policy interventions, and firm heterogeneity jointly constrain aggregate productivity gains. These insights provide an empirical foundation for the concluding chapter, where I synthesise the main findings and discuss implications for policy and future research.

6. Conclusion

Over the past decade, allocative efficiency in German manufacturing has deteriorated markedly, with COVID-19 accelerating pre-existing structural weaknesses, showing: There is a lost productivity potential. By leveraging harmonized firm-level microdata and integrating three complementary analytical frameworks—misallocation measures (Hsieh & Klenow, 2009), reallocation decompositions (Olley & Pakes, 1996), and markup estimation (Raval, 2023)—this study presents a comprehensive perspective on the interplay between factor market distortions, reallocation dynamics, and input-specific frictions. These findings offer novel insights into the persistent puzzle of unrealized productivity potential in the sector.

The evidence shows persistent and widening gaps in MRPs, especially for capital, indicating sustained frictions in capital allocation. These distortions are concentrated in large, capital-intensive sectors and intensified during the pandemic. Reallocation has weakened: the covariance term in the Olley and Pakes (1996)-decomposition declined steadily, particularly in 2020-2021, suggesting that high-productivity entrants faced scaling barriers while incumbents retained market share despite lower productivity. TFPR dispersion increased markedly from 2017 onward, spiking during COVID-19, with MRPC distortions outweighing labour distortions by scale. Markup estimates reveal parallel movements in labour and material markups until 2020, followed by pandemic-induced divergence and only partial reconvergence thereafter.

These patterns indicate that static misallocation, weakened reallocation dynamics, and asymmetric input frictions reinforce each other, compounding their negative impact on aggregate productivity. While allocative distortions capture inefficiencies in factor allocation, reallocation dynamics reflect whether high-productivity firms expand; the simultaneous rise in misallocation and fall in reallocation efficiency during crises signals both greater inefficiency and reduced corrective capacity.

From a policy perspective, improving aggregate productivity requires more than technological diffusion. First, reducing capital market frictions, e.g., expanding access to equity and long-term financing for productive SMEs, could lower the MRPC dispersion. Second, labour market reforms, such as more flexible short-time work schemes with conditionality, could preserve reallocation incentives during downturns. Third, competition policy should strengthen the link between productivity and market share to enable the scaling of high-productivity entrants. Finally, sector-specific measures to mitigate input distortions, e.g., diversifying supply chains and adopting digital supply chain tools, could reduce markup volatility, especially for materials. Embedding these steps in a coherent productivity strategy with regular monitoring would enable timely policy responses.

Interpretation of misallocation indicators warrants caution. Counterfactual gains from reducing the dispersion of TFPR may overstate the efficiency potential, as the model assumes frictionless reallocation. The dispersion in MRPC / MRPL may partially reflect genuine heterogeneity in technology, risk, or input quality. The dataset excludes informal and non-incorporated firms, possibly understating inefficiencies. Moreover, forcing rapid reallocation could generate negative externalities, especially in niche sectors or during automation-driven capital–labour substitution.

Future research should integrate physical output data to enable the quantity-based variant, extend the analysis to services and construction sectors, and test robustness under alternative production functions such as CES with capital–labour substitution. It should also examine the role of innovation and automation in driving substitution effects, employ a dynamic Olley and Pakes (1996)-decomposition with firm-level entry and exit, analyze markup dynamics using scanner or transaction-level data, and conduct cross-country comparisons with harmonized microdata to identify institutional drivers of allocative efficiency and misallocation.

The broader implication is that the challenge for Germany's manufacturing productivity lies less in technological capacity than in the inefficient deployment of existing resources. Without targeted reforms to ease capital and labour frictions and safeguard reallocation incentives, allocative inefficiency will continue to weigh on long-term growth. Enhancing allocative efficiency should not be treated as a narrow microeconomic issue but as a strategic priority to maintain productivity in the face of demographic change, technological disruption, and global competition.

List of Figures (Appendix)

Appendice

A Descriptive Figures

This section presents supplementary descriptive plots from Section 3.3. While not essential for the main empirical narrative, they provide further transparency regarding the sectoral, legal, and size structure of the matched JANIS–VGR dataset.

Key Results: Analysis Sample (2014–2022)

- **Firm coverage.** Final sample: 25,591 manufacturing firms (≈119,000 observations); unbalanced panel due to entry/exit ("submarine effect").
- **Firm dynamics.** Declining entry and rising exit across K/L quintiles (Fig. 7) ⇒ shrinking firm base; consistent with **H1:** declining allocative efficiency over time.
- **Size structure.** Employment and capital highly concentrated in medium/large firms; top capital quantile $>$80% of total K (Figs. 9–A.2) ⇒ distortions among large firms have outsized TFP impact.
- **VA.** Strong concentration mirrors capital (Figs. 10–A.3) ⇒ supports **H2:** misallocation in capital-intensive segments has larger aggregate effects.
- **Sectoral composition.** Coverage strong in CL (Motor Vehicles and Other Transport), CE+CF (Chemicals and Pharmaceuticals), CK (Machinery and Equipment) (Appendix A) ⇒ relevant for sectorally heterogeneous distortions (links to **RQ2**).
- **Firm age.** Average age 30–45 years; older in CA (Food, Beverages, Tobacco), CE+CF, CB (Textiles, Apparel, Leather); younger in CM (Furniture, Misc. Manufact., Repair), CI (Electronics and Optics), CL (Motor Vehicles and Other Transport) ⇒ **H3:** younger firms adjust more flexibly to distortions.
- **Panel duration.** $\sim$25% singletons vs. $\sim$25% full-period survivors ⇒ coexistence of persistent vs. transitory distortions (links to **RQ1/RQ3** on dynamics and distribution).

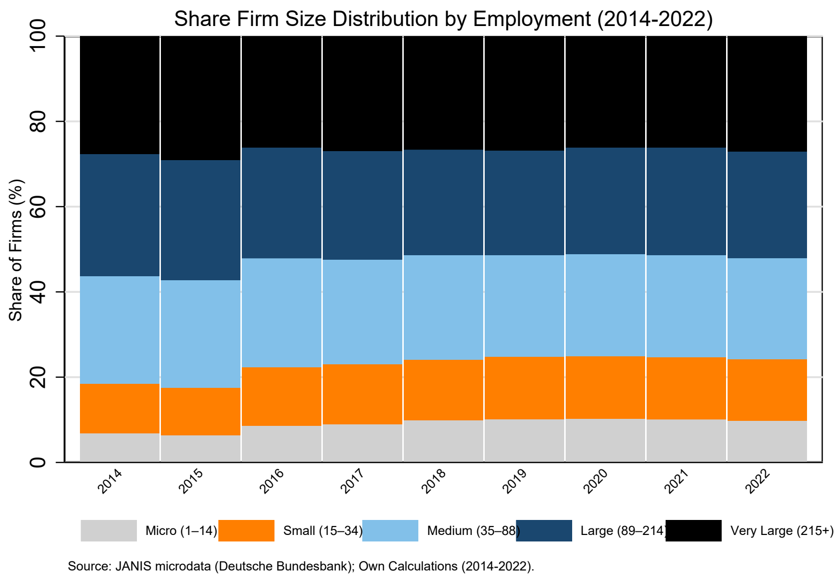


Figure A.1: Share of Employment by Firm Size Class in German Manufacturing (2014–2022). Source: JANIS microdata (Deutsche Bundesbank). Own calculations.

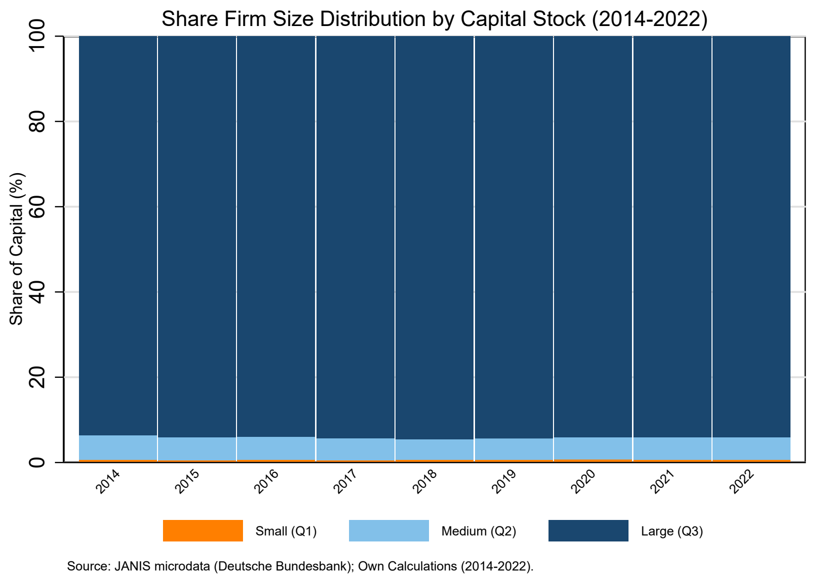


Figure A.2: Share of Capital Stock by Firm Size Class in German Manufacturing (2014–2022). Source: JANIS microdata (Deutsche Bundesbank). Own calculations.

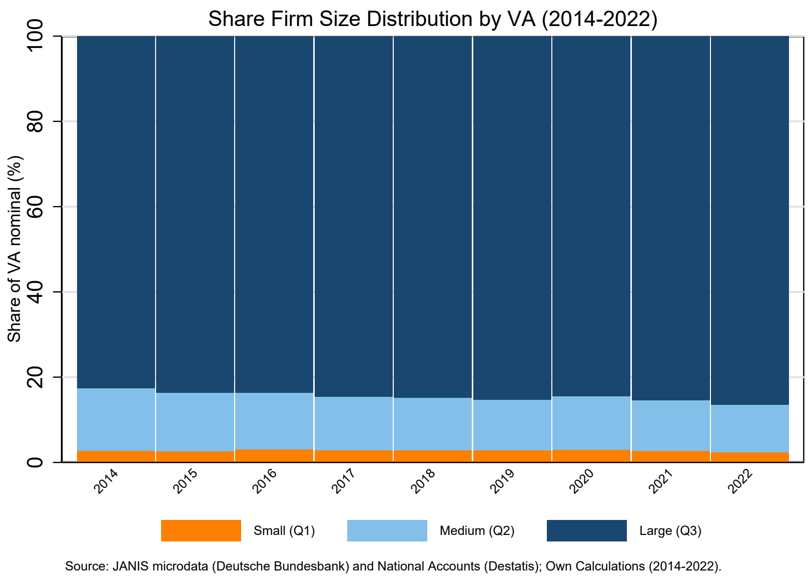


Figure A.3: Share of VA by Firm Size Class in German Manufacturing (2014–2022). Source: JANIS microdata (Deutsche Bundesbank). Own calculations.

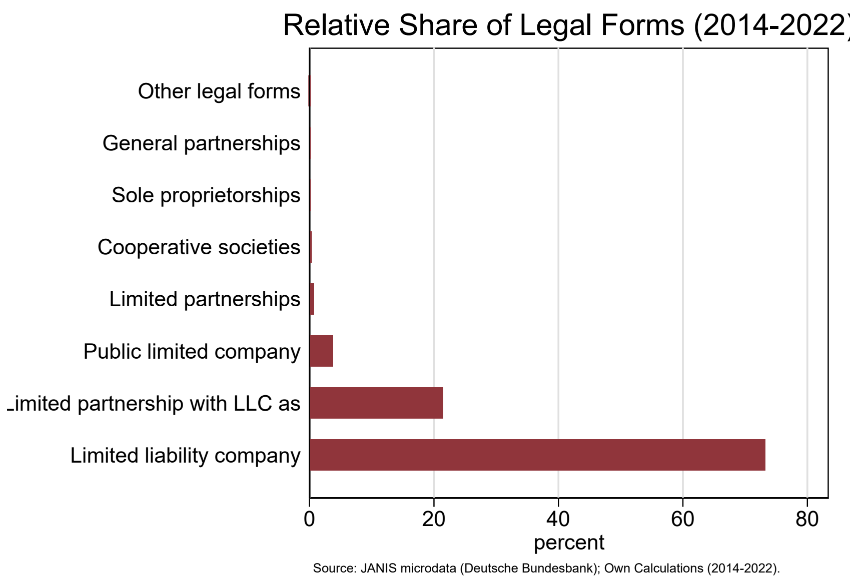


Figure A.4: Relative Share of Legal Forms among Firms in German Manufacturing (2014–2022). Source: JANIS microdata (Deutsche Bundesbank). Own calculations.

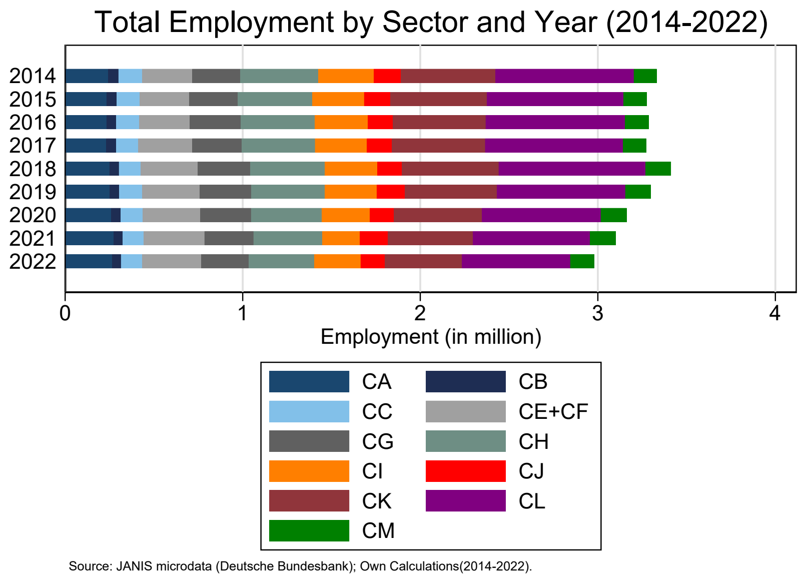


Figure A.5: Total Employment by Sector and Year in German Manufacturing (2014–2022). Source: JANIS microdata (Deutsche Bundesbank). Own calculations.

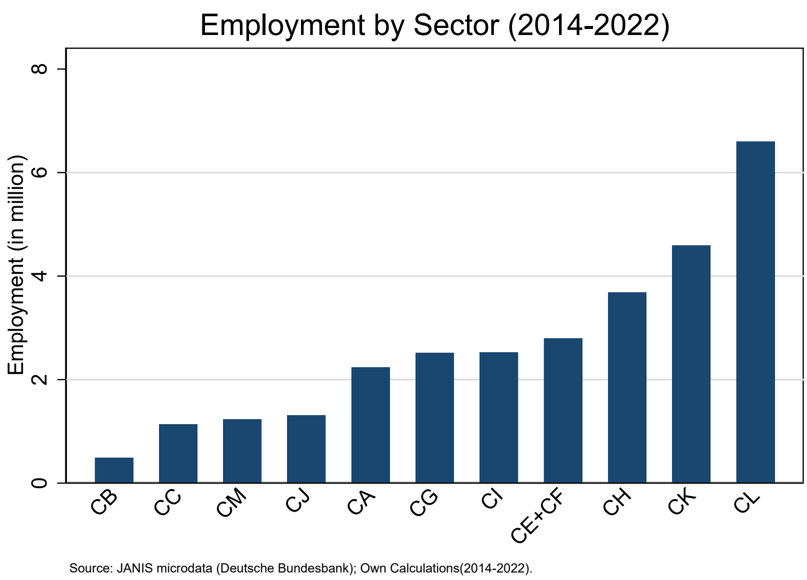


Figure A.6: Average Employment by Sector in German Manufacturing (2014–2022). Source: JANIS microdata (Deutsche Bundesbank). Own calculations.

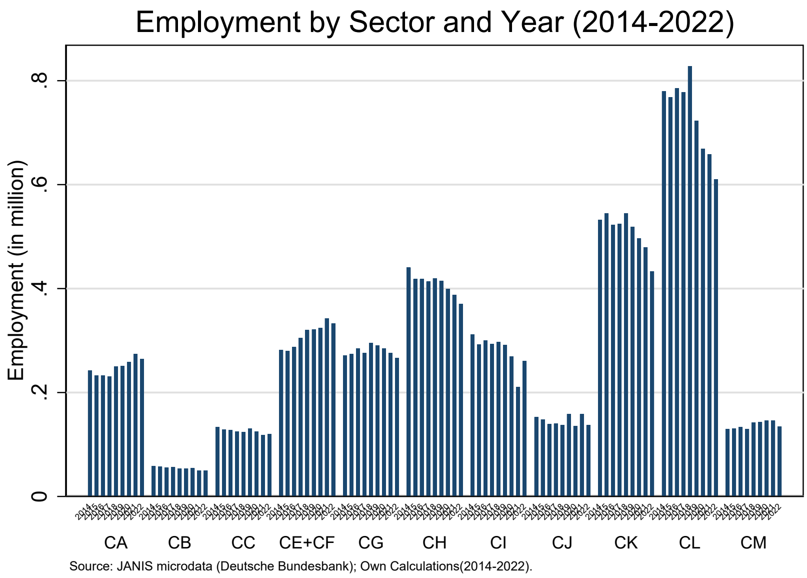


Figure A.7: Employment per Sector and Year in German Manufacturing (2014–2022). Source: JANIS microdata (Deutsche Bundesbank). Own calculations.

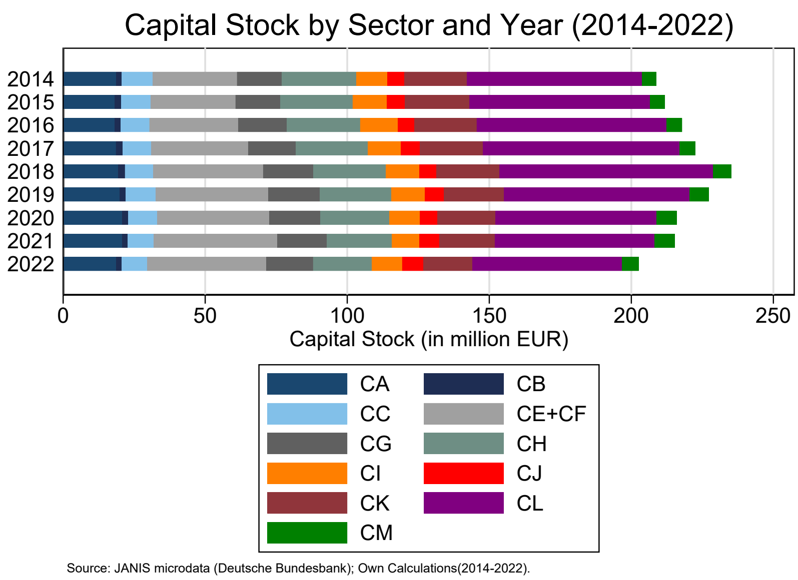


Figure A.8: Capital Stock by Sector and Year in German Manufacturing (2014–2022). Source: JANIS microdata (Deutsche Bundesbank). Own calculations.

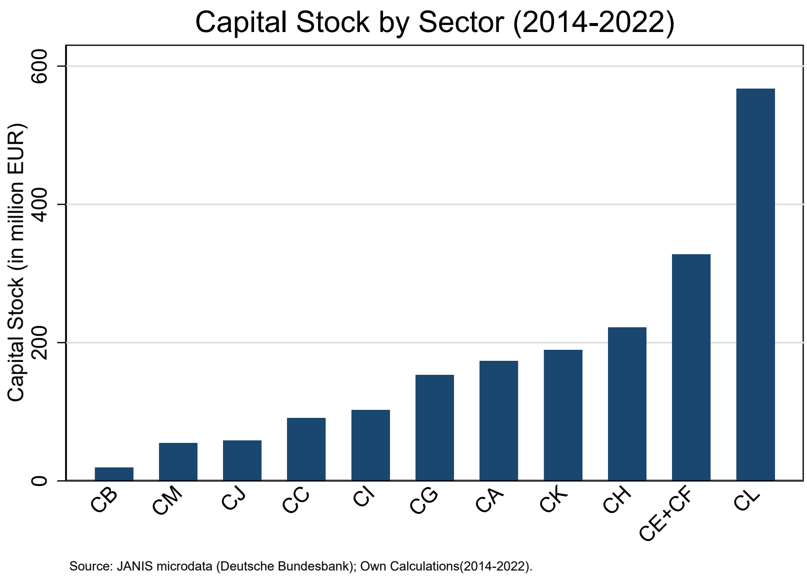


Figure A.9: Average Capital Stock by Sector in German Manufacturing (2014–2022). Source: JANIS microdata (Deutsche Bundesbank). Own calculations.

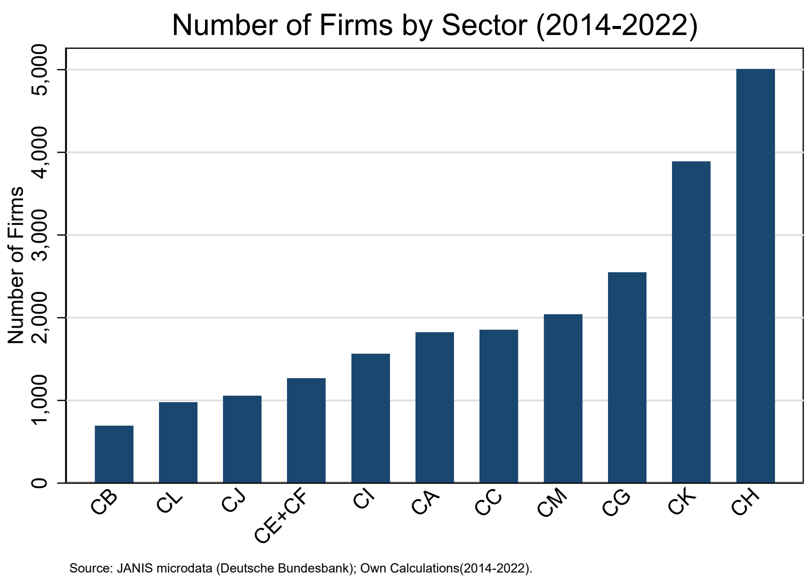


Figure A.10: Average Number of Firms by Sector in German Manufacturing (2014–2022). Source: JANIS microdata (Deutsche Bundesbank). Own calculations.

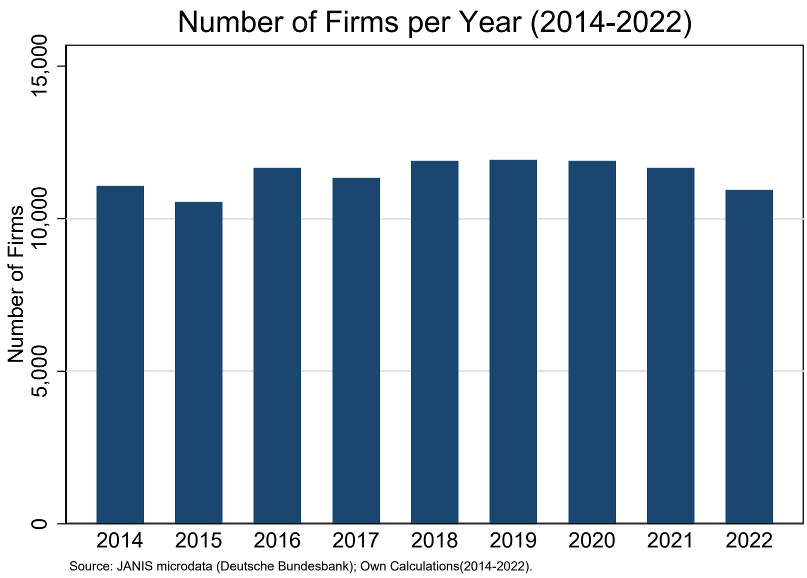


Figure A.11: Average Number of Firms by Year in German Manufacturing (2014–2022). Source: JANIS microdata (Deutsche Bundesbank). Own calculations.

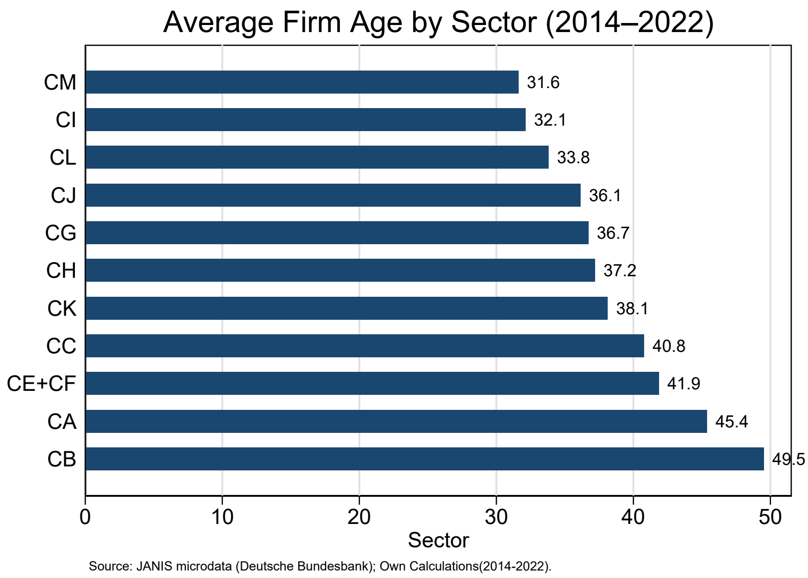


Figure A.12: Average Age of Firms in German Manufacturing (2014–2022). Source: JANIS microdata (Deutsche Bundesbank). Own calculations.

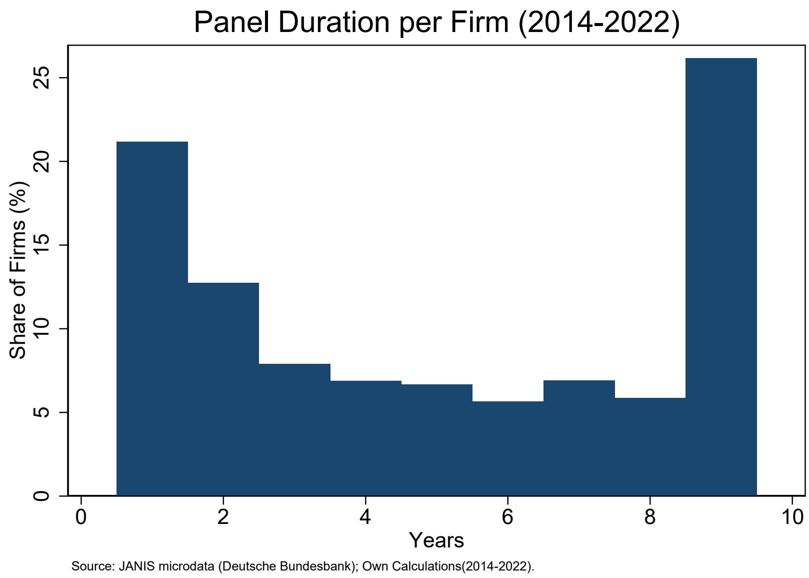


Figure A.13: Panel Duration of Firms in German Manufacturing (2014–2022). Source: JANIS microdata (Deutsche Bundesbank). Own calculations.

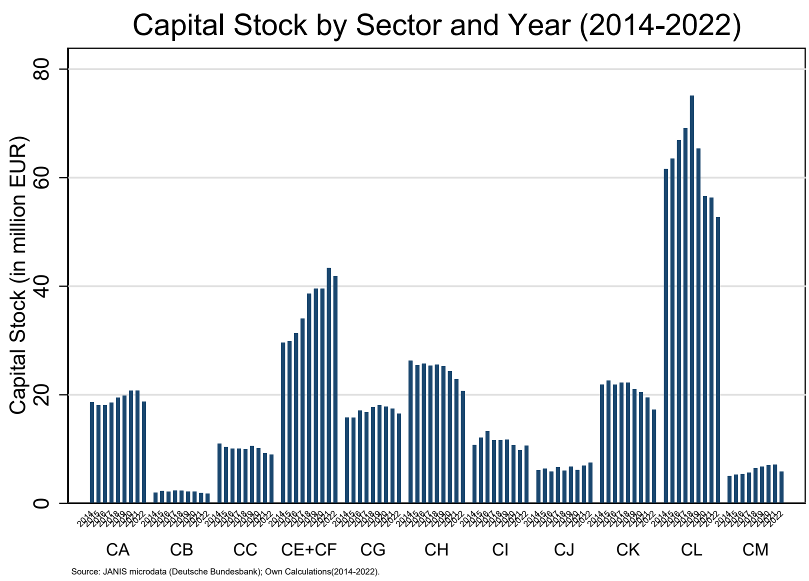


Figure A.14: Firm Count per Sector and Year in German Manufacturing (2014–2022). Source: JANIS microdata (Deutsche Bundesbank). Own calculations.

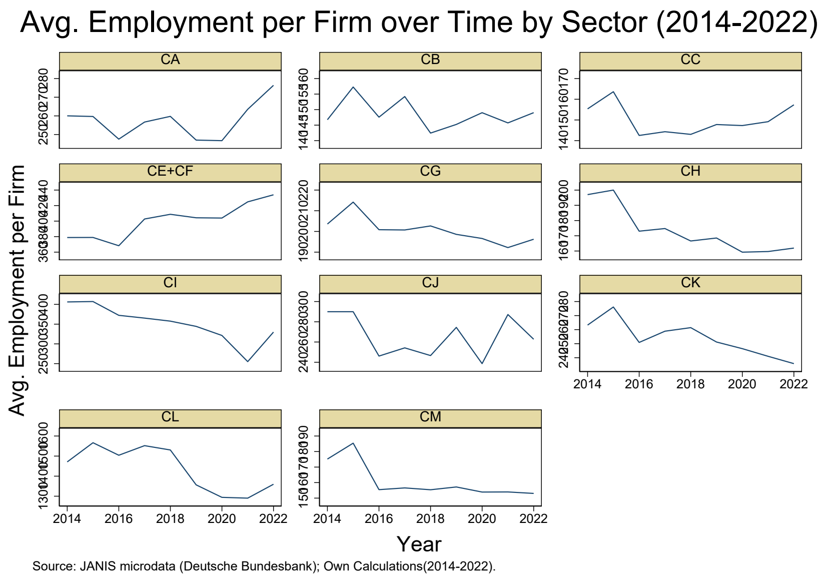


Figure A.15: Average Employment per Firm by Sector over Time in German Manufacturing (2014–2022). Source: JANIS microdata (Deutsche Bundesbank). Own calculations.

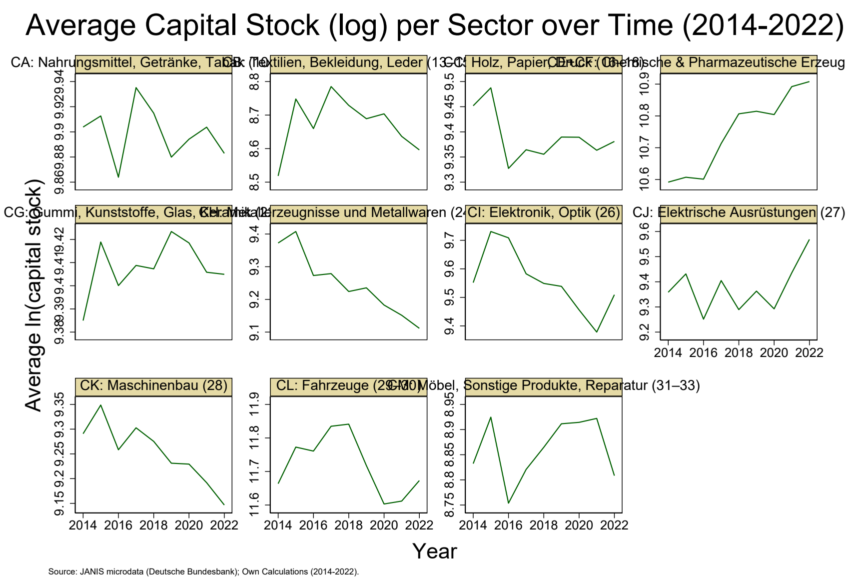


Figure A.16: Average Capital Stock per Firm by Sector over Time in German Manufacturing (2014–2022). Source: JANIS microdata (Deutsche Bundesbank). Own calculations.

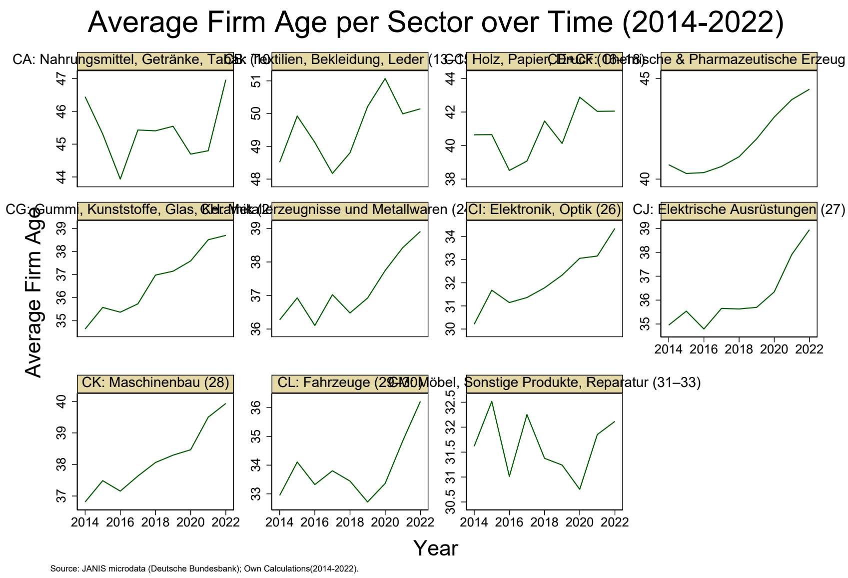


Figure A.17: Average Firm Age by Sector over Time in German Manufacturing (2014–2022). Source: JANIS microdata (Deutsche Bundesbank). Own calculations.

B Empirical Implementation

B.1 Research Questions and Hypotheses

RQ and Hs

Frameworks used: HK = Hsieh and Klenow (2009) (sales-based variant Calligaris et al. (2018)); OP = Altomonte and Di Mauro (2022); Olley and Pakes (1996); Raval = Raval (2023).

- **RQ1 (HK):** How did allocative efficiency and misallocation in German manufacturing evolve between 2014–2022, particularly during COVID-19?
- **RQ2 (HK, heterogeneity):** Which firm-level and sectoral features explain dispersion and how did crisis shocks change these patterns?
- **RQ3 (OP):** How did the reallocation dynamics change during the COVID-19 Pandemic and how are they linked to shifts in firm composition?
- **RQ4 (Raval):** Do factor-specific markups deviate and diverge during disruptions, indicating input-specific distortions?

Hypotheses

- **H1 (HK):** Sectoral TFPR dispersion increased over 2014–2022 and especially during COVID-19 $\Rightarrow$ allocative inefficiency rose.
- **H2 (HK):** Capital distortions contribute more to observed misallocation than labour distortions.
- **H3 (HK, heterogeneity):** Misallocation displays strong heterogeneity across sectors and firm sizes; crisis shocks exacerbate existing inefficiencies.
- **H4 (OP):** The Olley and Pakes (1996)-covariance term weakened during COVID-19 (smaller Olley and Pakes (1996)-gap), with incumbents retaining market shares despite lower productivity and high-productivity entrants facing expansion barriers.
- **H5 (Raval):** Labour and material markups diverged more strongly during periods of disruption $\Rightarrow$ input-specific distortions.

B.2 Hsieh & Klenow (2009): Misallocation Framework

Key Results: Misallocation in German Manufacturing, 2014–2022

- Persistent increase in TFPR dispersion since 2018, peaking during COVID-19.
- Capital misallocation (MRPC dispersion) exceeds labour misallocation (MRPL) in scale, both great dispersion.
- Pandemic-related policies stabilised output but prolonged allocative inefficiencies.
- Aggregate TFP efficiency gap reached 5% in 2020, remains at elevated level.
- Frontier–laggard divergence widened post-2018, with laggards dragging aggregate productivity.

The empirical implementation proceeds in the following steps:

Step 1: Constructing VA. Firm-level nominal VA is defined as:

$$VA_{si}^{\text{nom}} = \text{sales}_{si} - \text{intermediate inputs}_{si}, \tag{21}$$

where s indexes sectors and i indexes firms. To control for inflation and sector-specific price dynamics, nominal values are converted into constant prices using sector-year gross VA deflators from the VGR:

$$VA_{si}^{\text{real}} = \frac{VA_{si}^{\text{nom}}}{\text{Deflator}_{st}} \times 100. \tag{22}$$

Step 2: Estimating Factor Shares. In the Cobb–Douglas framework, the sector-specific capital elasticity α_s is inferred from the observed labour cost share, following Calligaris et al. (2018) and De Loecker and Goldberg (2014):

$$\alpha_s = 1 - \frac{\text{wagebill}_{si}}{VA_{si}^{\text{nom}}}, \tag{23}$$

where wagebill_{si} includes wages, salaries, bonuses, and employer social contributions. The ratio in (23) is aggregated to the sector-year level to mitigate measurement error.

Step 3: Computing TFP. Firm-level TFP in Calligaris et al. (2018); Hsieh and Klenow (2009) is obtained as the residual derived from estimation of a Cobb–Douglas production function:

$$TFP_{si} = \frac{VA_{si}}{K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}}, \tag{24}$$

where K_{si} and L_{si} are firm-level capital and labour inputs, and α_s is taken from Equation (23). Two variants are distinguished:

- $TFPR$: Equation (24) with $VA_{si} = VA_{si}^{\text{nom}}$ from Equation (21).
- **Quantity-based productivity ($TFPQ$)**: Equation (24) with $VA_{si} = VA_{si}^{\text{real}}$ from Equation (22).

Step 4: Allocative Efficiency and Misallocation. Following Hsieh and Klenow (2009), within sector dispersion in revenue productivity is measured as:

$$\text{Var}(\ln TFPR_{si}), \tag{25}$$

and the aggregate TFP gap relative to the efficient allocation is computed as:

$$\frac{TFP^*}{TFP} = \prod_s \left[\frac{\overline{TFPR}_s}{\left(\prod_{i \in s} TFPR_{si}^{\theta_{si}}\right)} \right]^{\theta_s}, \tag{26}$$

with θ_s denoting the sectoral share of total VA.

Step 5: Revenue Productivity (TFPR) and Consistency Check. Revenue productivity is defined as:

$$TFPR_{si} = \frac{VA_{si}^{\text{nom}}}{K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}}, \tag{27}$$

where VA_{si}^{nom} is nominal VA from Equation (21), K_{si} and L_{si} are firm-level capital and labour inputs, and α_s is the sector-specific capital elasticity from Equation (23).

In a frictionless, competitive market, $TFPR_{si}$ would be identical across all firms i within sector s. Dispersion in $\ln TFPR_{si}$, as in Equation (25), is therefore an indicator of resource misallocation (Calligaris et al., 2018; Hsieh & Klenow, 2009).

Step 6: Consistency with MRPs. In a Cobb–Douglas production setting, TFPR reflects a weighted geometric mean, combining MRPC and MRPL according to their elasticities in the production function Calligaris et al. (2018); Hsieh and Klenow (2009):

$$TFPR_{si} = (MRPC_{si})^{\alpha_s} \cdot (MRPL_{si})^{1-\alpha_s}, \tag{28}$$

where $MRPC_{si}$ and $MRPL_{si}$ are given by:

$$MRPC_{si} = \frac{\alpha_s \cdot VA_{si}^{\text{nom}}}{K_{si}}, \tag{29}$$

$$MRPL_{si} = \frac{(1-\alpha_s) \cdot VA_{si}^{\text{nom}}}{L_{si}}. \tag{30}$$

As a validation step, I compute the firm-level ratio:

$$\frac{TFPR_{si}}{(MRPC_{si})^{\alpha_s} \cdot (MRPL_{si})^{1-\alpha_s}}, \tag{31}$$

and evaluate its proximity to unity across the sample. Values close to one indicate internal consistency of the estimated productivity and MRP measures. Systematic deviations may signal measurement error, misspecification of elasticities, or violations of constant returns to scale.

Step 7: Sectoral Productivity Aggregation. Following Hsieh and Klenow (2009) and Calligaris et al. (2018), sector-level productivity is aggregated using a constant elasticity of substitution (CES) framework that accounts for within sector distortions:

$$A_s = \left(\sum_{i \in s} A_{si} \left(\frac{\overline{TFPR}_s}{TFPR_{si}} \right)^{\sigma-1} \right)^{\frac{1}{\sigma-1}}, \tag{32}$$

where $\sigma = 3$ denotes the elasticity of substitution across firm varieties. This formulation captures the efficiency loss from misallocation by penalizing deviations of firm-level revenue productivity from the sectoral benchmark $\overline{TFPR}_s$.

Step 8: Firm-Level Physical Productivity. Firm-specific physical productivity A_{si} is computed as the residual from a Cobb-Douglas production function using deflated output and observed input quantities:

$$A_{si} = \frac{VA_{si}^{\text{real}}}{K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}}, \tag{33}$$

where VA_{si}^{real} is real VA (Equation (**??**)), K_{si} is the real capital stock, L_{si} is the number of employees, and α_s is the sector-specific capital elasticity from Equation (23).

Step 9: Sectoral Benchmark TFPR. The benchmark revenue productivity $\overline{TFPR}_s$ is defined as the weighted geometric mean of firm-level TFPR values:

$$\overline{TFPR}_s = \prod_{i \in s} TFPR_{si}^{\theta_{si}}, \tag{34}$$

where θ_{si} represents the firm's weight, typically based on its share of sectoral sales or set uniformly. This benchmark reflects the frictionless equilibrium level of revenue productivity and serves as a reference point for evaluating allocative distortions within the sector.

Step 10: Benchmark MRPs. Analogously to the sectoral benchmark for revenue productivity, benchmark values for the MRPC and MRPL are defined as:

$$\overline{MRPC}_s = \prod_{i\in s} MRPC_{si}^{\theta_{si}}, \quad \overline{MRPL}_s = \prod_{i\in s} MRPL_{si}^{\theta_{si}}, \tag{35}$$

where $\theta_{i,s}$ denotes the firm-specific weight, e.g. based on the share in sectoral sales. These benchmarks represent the sector-level returns to capital and labour under an efficient allocation.

In empirical work, these theoretical benchmarks are often approximated by unweighted arithmetic means across firms within sector–year cells:

$$\overline{X}_s \approx \frac{1}{N_s} \sum_{i\in s} X_{si}, \quad X \in \{\text{TFPR, MRPC, MRPL}\}, \tag{36}$$

and, for log-transformed values:

$$\ln \overline{X}_s \approx \frac{1}{N_s} \sum_{i\in s} \ln X_{si}, \quad X \in \{\text{TFPR, MRPC, MRPL}\}. \tag{37}$$

While geometric means are consistent with the CES aggregation structure in the theoretical model, arithmetic means are widely used in empirical applications due to their computational simplicity and direct interpretability in log-variance decompositions (Bartelsman et al., 2013; Calligaris et al., 2018).

Step 11: Aggregate and Counterfactual Productivity. To assess the productivity potential under an efficient allocation of resources, a counterfactual sector-level productivity measure is constructed. Following Calligaris et al. (2018), this efficient productivity level assumes that all firms within a sector face identical input prices—i.e., that firm-level TFPR values are equalized. Under this scenario, the counterfactual aggregate productivity is computed as:

$$A_s^* = \left(\sum_{i\in s} A_{si}^{\sigma-1} \right)^{\frac{1}{\sigma-1}}, \tag{38}$$

where

$$A_{si} = \frac{VA_{si}^{\text{REAL}}}{K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}}$$

denotes firm-level physical productivity, computed from *real* VA (VA^{REAL}), capital K (book-value-based fixed assets), and labour L (employment per headcount). The elasticity of substitution across firm varieties σ is set to the standard value of 3, in line with empirical applications in the misallocation literature (Bartelsman et al., 2013; Hsieh & Klenow, 2009; Restuccia & Rogerson, 2013).

The measure A_s^* captures the productivity level that would prevail in sector s in the absence of any distortions in factor allocation. Comparing A_s and A_s^* allows for the quantification of the TFP loss due to misallocation.

To obtain an aggregate measure of productivity at the national level, sectoral productivity levels are combined using fixed output weights θ_s, which are derived from *real* sectoral sales of VA ($VA^{\text{SALES,REAL}}$) in the base year 2020. Following Calligaris et al. (2018), aggregate observed and counterfactual TFP are computed as:

$$\ln(TFP_t) = \sum_s \theta_s \cdot \ln(A_s), \quad \ln(TFP_t^*) = \sum_s \theta_s \cdot \ln(A_s^*). \tag{39}$$

The difference $\ln(TFP_t^*) - \ln(TFP_t)$ represents the economy-wide productivity loss attributable to misallocation.

In line with Hsieh and Klenow (2009), this productivity gap can also be interpreted as a reduction in aggregate output caused by allocative inefficiency. Specifically, the ratio of observed to efficient output is expressed as:

$$\frac{Y}{Y^*} = \prod_{s=1}^{S} \left(\frac{A_s}{A_s^*}\right)^{\theta_s} = \prod_{s=1}^{S} \left[\sum_{i=1}^{N_s} \left(\frac{A_{si}}{A_s} \cdot \frac{\overline{TFPR_s}}{TFPR_{si}}\right)^{\sigma-1}\right]^{\frac{\theta_s}{\sigma-1}}. \tag{40}$$

Equivalently, this relationship can be expressed in terms of TFP aggregates:

$$\frac{TFP}{TFP^*} = \frac{\prod_{s=1}^{S} (A_s)^{\theta_s}}{\prod_{s=1}^{S} (A_s^*)^{\theta_s}}, \tag{41}$$

which implies that gains in allocative efficiency—reflected by a convergence of firm-level TFPR values $\left(\frac{VA^{\text{NOM}}}{K^{\alpha_s} L^{1-\alpha_s}}\right)$ toward the sectoral benchmark—translate directly into increases in aggregate output.

The logarithmic form of this relationship provides a particularly intuitive interpretation:

$$\ln\left(\frac{Y}{Y^*}\right) = \ln\left(\frac{TFP}{TFP^*}\right) = \sum_{s=1}^{S} \theta_s \cdot (\ln A_s - \ln A_s^*), \tag{42}$$

highlighting the role of sector-specific inefficiencies in shaping the macroeconomic performance of the economy.

Step 12: Measuring Input Misallocation Following Hsieh and Klenow (2009), I assess input misallocation within sectors by computing the dispersion of log-transformed TFPR and the MRPC and MRPL.

Allocative inefficiency is captured by the squared deviation of firm-level TFPR from the sectoral benchmark:

$$\left(\ln TFPR_{si} - \ln \overline{TFPR_s}\right)^2, \tag{43}$$

where equal TFPR across firms is a necessary condition for efficiency.

Capital- and labour-specific distortions are measured analogously:

$$\left(\ln MRPC_{si} - \ln \overline{MRPC_s}\right)^2, \quad \left(\ln MRPL_{si} - \ln \overline{MRPL_s}\right)^2. \tag{44}$$

Each observation is weighted by its nominal value-added share within the sector:

$$w_{ist} = \frac{VA_{sit}^{\text{NOM}}}{\sum_{i \in s} VA_{sit}^{\text{NOM}}}, \tag{45}$$

ensuring that larger firms have proportionally greater influence on the dispersion measures (Bartelsman et al., 2013; Calligaris et al., 2018).

The weighted variances of $\ln TFPR$, $\ln MRPC$, and $\ln MRPL$ are computed annually, enabling the tracking of allocative efficiency over time and the identification of crisis periods or sector-specific patterns linked to heightened misallocation.

Step 13: Sectoral and Aggregate Dispersion Measures. Analogously to the benchmark definitions in Step 10, dispersion measures can be computed for TFPR as well as the MRPC and MRPL. The sector-level weighted variance for a generic performance measure $X \in \{\text{TFPR}, \text{MRPC}, \text{MRPL}\}$ is defined as:

$$\text{Var}_s(\ln X_{si}) = \sum_{i \in s} w_{sit} \cdot \left(\ln X_{si} - \ln \overline{X}_{st}\right)^2, \tag{46}$$

where w_{sit} denotes the nominal value-added weight from Equation 45 and $\overline{X}_{st}$ is the sectoral benchmark from Equations 35–37. This formulation quantifies the output-weighted deviation of each firm from the sectoral mean, capturing its contribution to within sector misallocation.

To obtain aggregate dispersion measures, sectoral variances are combined using fixed sectoral output shares θ_s:

$$\text{Var}(\ln X_t) = \sum_s \theta_s \cdot \text{Var}_s(\ln X_{si}), \quad X \in \{\text{TFPR}, \text{MRPC}, \text{MRPL}\}. \tag{47}$$

Here, θ_s is based on sectoral value-added sales.

B.3 Olley & Pakes (1996): Decomposition Framework

Key Results: ( )-Decomposition

- **Within-firm efficiency as main driver:** From 2014–2022, productivity growth in German manufacturing was largely attributable to improvements within-firms, with reallocation playing a secondary role.
- **Reallocation weak and unstable:** Between-firm contributions were mostly small or negative, briefly turning positive in 2021 before stagnating again in 2022.
- **Deviation from theoretical expectations:** Contrary to standard models predicting a cleansing effect after major shocks, postcrisis reallocation remained muted.
- **Policy context:** The results are consistent with evidence that extensive government support—such as credit guarantees, ultra-low interest rates, and liquidity provision—shielded low-productivity incumbents and dampened market selection pressures, thereby constraining reallocation mechanisms.

The decomposition is implemented in the following steps:

Step 1: Sample Selection I restrict the sample to manufacturing firms (WZ08: 10–33), consistent with the Hsieh and Klenow (2009) implementation. Each firm is assigned its most frequent 2-digit WZ08 sector code. Sectors with fewer than 100 observations in a given year are excluded to ensure robustness.

Step 2: Variable Construction Firm-level productivity measures are computed for both variants:

- **LP:** real VA from the JANIS dataset per full-time equivalent employee.
- **TFP:** as computed in the Hsieh & Klenow (2009) implementation, based on real output, real inputs, and user-cost-adjusted capital.

Log transformations are applied to reduce skewness, and variables are winsorized at the 1st and 99th percentiles within each sector-year to mitigate the influence of extreme values.

In all subsequent formulas, P_{it} denotes the productivity measure used in the decomposition, which takes two alternative forms:

1. **LP:**

$$P_{it} = LP_{it} = \frac{VA_{it}^{\text{real}}}{L_{it}} \tag{48}$$

2. **TFP:**

$$P_{it} = TFP_{it} \tag{49}$$

as computed in the Hsieh & Klenow (2009) framework described in Section 4..

The use of P_{it} in generic notation allows a uniform presentation of the decomposition equations, while maintaining full comparability between the LP and TFP variants.

Step 3: Weight Definition Following **?**, firm-level employment shares are defined as:

$$s_{it} = \frac{L_{it}}{\sum_{j\in S_t} L_{jt}}, \tag{50}$$

where L_{it} is employment in firm i at time t, and S_t denotes the set of all firms in the sector in year t. For comparisons, I use average weights across two consecutive years:

$$\bar{s}_{it} = \frac{1}{2}(s_{it} + s_{i,t-1}). \tag{51}$$

As a robustness check, I repeat the decomposition using value-added shares instead of employment shares to assess the sensitivity of results to the weighting scheme.

Step 4: Within-Firm Component The *within* component captures average productivity growth of incumbent firms:

$$\text{Within} = \sum_{i\in C} \left(\Delta \ln P_{it} \cdot \bar{s}_{it}\right), \tag{52}$$

where C is the set of continuing firms between $t-1$ and t.

Step 5: Between-Firm Component The *between* component measures changes in employment shares weighted by average productivity:

$$\text{Between} = \sum_{i\in C} \left(\frac{1}{2}(\ln P_{it} + \ln P_{i,t-1}) \cdot \Delta s_{it}\right), \tag{53}$$

where $\Delta s_{it} = s_{it} - s_{i,t-1}$. A positive value indicates reallocation toward more productive firms.

Step 6: Aggregate Productivity Change and Olley and Pakes (1996)-gap Check Aggregate productivity growth is computed as:

$$\Delta \ln P_t^{\text{agg}} = \sum_i (\ln P_{it} \cdot s_{it}) - \sum_i (\ln P_{i,t-1} \cdot s_{i,t-1}), \tag{54}$$

and verified to be closely approximated by the sum of the within and between components. As an additional consistency check, I compute the Olley and Pakes (1996)-gap

$$\text{OP-Gap}_t = \sum_i (s_{it} - \bar{s}_t)(\ln P_{it} - \ln \bar{P}_t),$$

to capture the static allocation component in each year.

Step 7: Sectoral Aggregation All components are calculated at the 2-digit WZ08 sector level and aggregated to the manufacturing sector using sectoral employment weights.

B.4 Raval (2023): Markup Estimation

Key Results: Markup Analysis

] **Dispersion Patterns (P90/P50):** Material markups are persistently more dispersed than labour markups (avg. gap $\approx$ 0.2 points). Dispersion peaked in 2020 for materials (≈ 2.05) while labour dispersion dropped to ≈ 1.63, indicating asymmetric input-specific shocks.
Time Trends:

- Labour markups: Modest volatility pre-2019, +3.3% in 2020 (p<0.01) due to wage rigidities/short-time work, then -6.1% in 2022.
- Material markups: Steady rise from 2015, +8.6% in 2020 (p<0.01) under supply-chain bottlenecks, partial correction (-2.8%) in 2022.

Cross-Input Correlation: Elasticity $\hat{\beta} = 0.561$ (p<0.01), above U.S. baseline (0.4–0.5), suggesting stronger co-movement of distortions across inputs in Germany. Within-R^2 = 0.391.

- During the pandemic, synchronized distortions in labour and material markups became more evident. Institutional features (sectoral bargaining, coordinated supply chains, regulation) likely reinforced persistence and synchronisation of markups.
- Elevated and asymmetric markup dispersion during disruptions supports **H5** and highlights multi-dimensional inefficiencies (**RQ4**) not captured by TFPR or Olley and Pakes (1996)-gap measures alone.

The estimation follows four main steps:

Step 1: Construction of Revenue Cost Shares. For each firm i in year t, nominal revenue cost shares are computed for labour and materials:

$$s_{it}^{L} = \frac{\text{Wagebill}_{it}}{\text{Sales}_{it}}, \tag{55}$$

$$s_{it}^{M} = \frac{\text{Intermediate Inputs}_{it}}{\text{Sales}_{it}}, \tag{56}$$

where Sales denotes nominal revenue, Wagebill represents total labour compensation (wages plus social security), and Intermediate Inputs captures expenditure on materials and services. All variables are obtained from the JANIS firm-level balance sheet dataset.

Step 2: Estimation of Output Elasticities. The production function is specified as:

$$\ln Y_{it} = \beta_0 + \beta_K \ln K_{it} + \beta_{L,it} \ln L_{it} + \beta_{M,it} \ln M_{it} + \omega_{it} + \varepsilon_{it}, \tag{57}$$

where Y_{it} is real output (sales deflated by the sectoral output deflator `deflator_prodval`), K_{it} is the real capital stock (constructed via the perpetual inventory method), L_{it} is labour input, and M_{it} is real intermediate materials input. From this estimation, the firm-specific coefficients $\hat{\theta}_{it}^{L}$ and $\hat{\theta}_{it}^{M}$ are recovered as output elasticities.

Step 3: Calculation of Factor-Specific Markups. Markups are computed by dividing the estimated output elasticity by the observed cost share:

$$\mu_{it}^L = \frac{\hat{\theta}_{it}^L}{s_{it}^L}, \tag{58}$$

$$\mu_{it}^M = \frac{\hat{\theta}_{it}^M}{s_{it}^M}. \tag{59}$$

This yields separate measures of pricing power for labour and materials, capturing potential factor-specific distortions. For aggregation, I compute weighted averages across all manufacturing firms using employment weights S_i, so that larger firms have proportionally greater influence on the aggregate markup.

Step 4: Panel Regression Analysis. Following (Raval, 2023), I examine the empirical relationship between factor-specific markups using a fixed-effects panel regression:

$$\ln(\mu_{it}^L) = \beta \ln(\mu_{it}^M) + \gamma_t + \delta_s + \alpha_i + \epsilon_{it}, \tag{60}$$

where γ_t are year fixed effects, δ_s are 2-digit sector fixed effects, and α_i are firm fixed effects. To analyse the time trends in each markup separately, I estimate:

$$\ln(\mu_{it}^X) = \gamma_t + \delta_s + \alpha_i + \epsilon_{it}, \quad \text{for } X \in \{L, M\}. \tag{61}$$

Under efficient allocation, factor markups should converge across inputs, implying $\mu^L \approx \mu^M$ within sectors. Divergence between labour and material markups—especially during periods of high TFPR dispersion in the HK analysis— would indicate the presence of output distortions that complement the input distortions measured by TFPR. Thus, the Raval framework provides a complementary lens to assess allocative efficiency in German manufacturing over 2014–2022, focusing on the convergence or divergence of factor-specific markups over time, including during shocks such as the COVID-19 pandemic.

Extension. The empirical specification extends the Hsieh and Klenow (2009) framework by incorporating input-specific markups estimated following Raval (2023). I estimate the following fixed-effects panel regression:

$$\ln(Y_{it}) = \beta_L \ln(\mu_{i,t-1}^L) + \beta_M \ln(\mu_{i,t-1}^M) + \gamma_t + \delta_s + \alpha_i + \varepsilon_{it}, \tag{62}$$

where μ^L and μ^M denote labour and material markups, respectively, and Y_{it} is either (i) TFPR$_{it}$, measuring allocative efficiency within sectors, or (ii) TFP$_{it}$, measuring quantity-based productivity. Both measures are computed following (Hsieh & Klenow, 2009).

Lagged markups are included to address potential simultaneity and reverse causality concerns, ensuring that contemporaneous productivity shocks do not mechanically affect measured markups. Year fixed effects (γ_t) control for macroeconomic shocks, sector fixed effects (δ_s) capture persistent industry-specific differences, and firm fixed effects (α_i) absorb time-invariant heterogeneity. Standard errors are clustered at the firm-level.

C Robustness Checks

C.1 Observation Window

This appendix section presents robustness checks to verify that the main findings are not driven by the specific choice of the observation window. By applying an alternative time period and base year for index normalisation, it is shown that the underlying patterns remain consistent across samples, confirming that the results are not an artefact of the selected time frame.

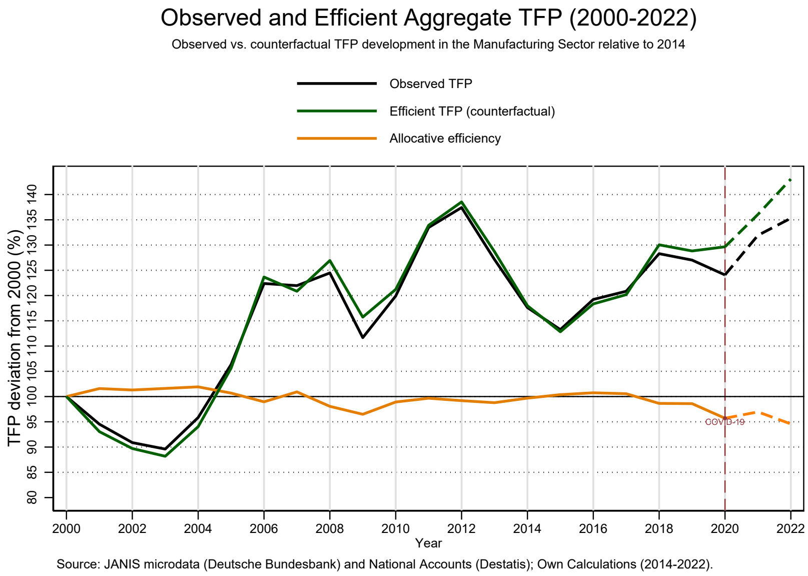


Figure C.18: Observed vs. Efficient TFP and Allocative Losses in German Manufacturing (relative to 2000). Source: JANIS microdata (Deutsche Bundesbank) and VGR (Destatis). Own calculations.

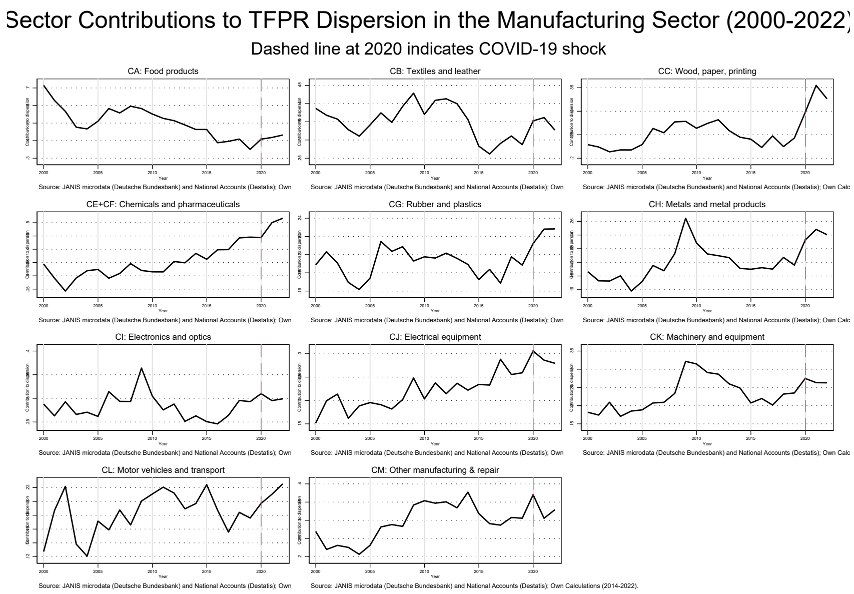


Figure C.19: Sectoral Contributions to TFPR Dispersion in German Manufacturing (relative to 2000). Source: JANIS microdata (Deutsche Bundesbank) and VGR (Destatis). Own calculations.

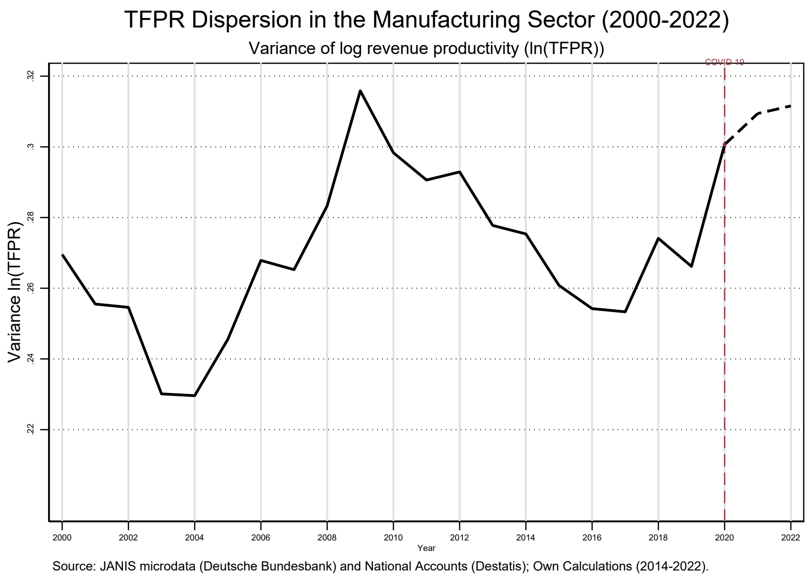


Figure C.20: Dispersion of TFPR in German Manufacturing (relative to 2000). Source: JANIS microdata (Deutsche Bundesbank) and VGR (Destatis). Own calculations.

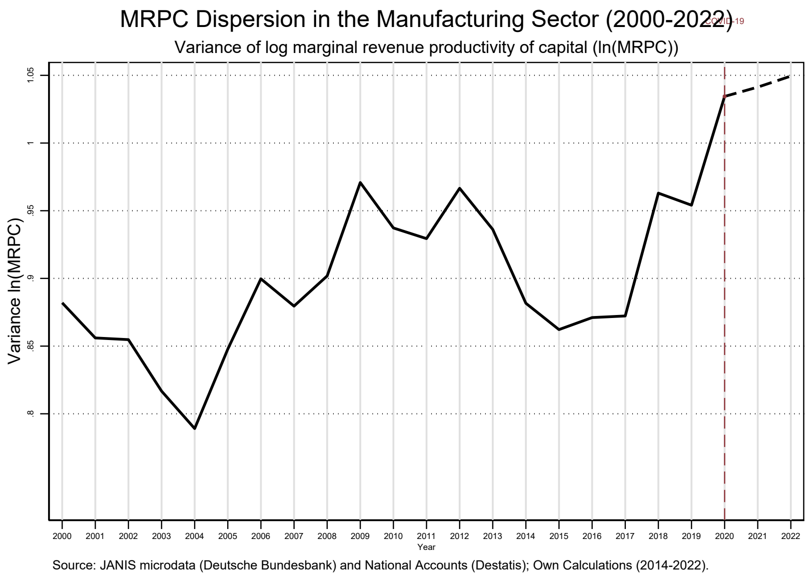


Figure C.21: Dispersion of MRPC in German Manufacturing (relative to 2000). Source: JANIS microdata (Deutsche Bundesbank) and VGR (Destatis). Own calculations.

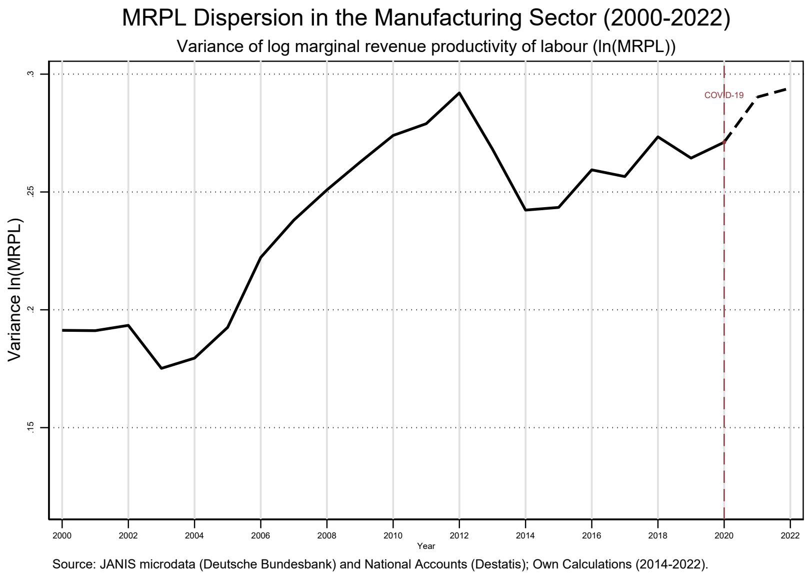


Figure C.22: Dispersion of MRPL in German Manufacturing (relative to 2000). Source: JANIS microdata (Deutsche Bundesbank) and VGR (Destatis). Own calculations.

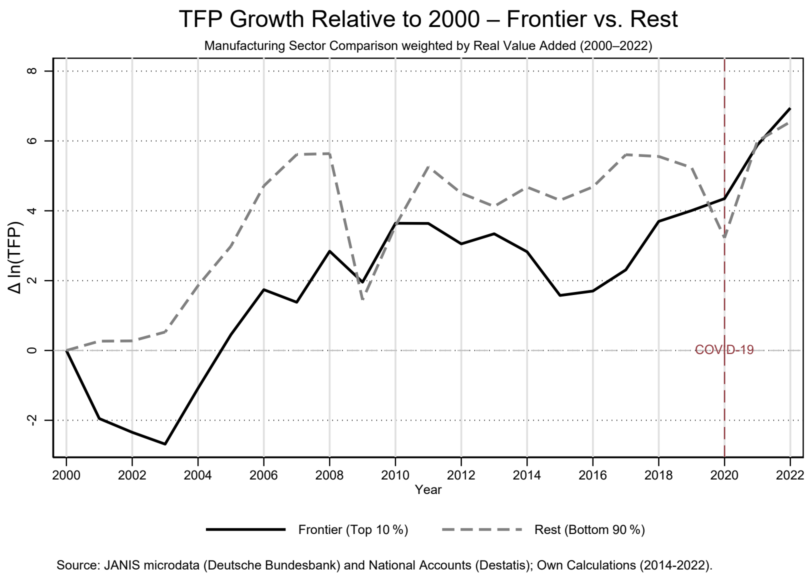


Figure C.23: TFPQ of Frontier vs. Rest Firms in German Manufacturing (relative to 2000). Source: JANIS microdata (Deutsche Bundesbank) and VGR (Destatis). Own calculations.

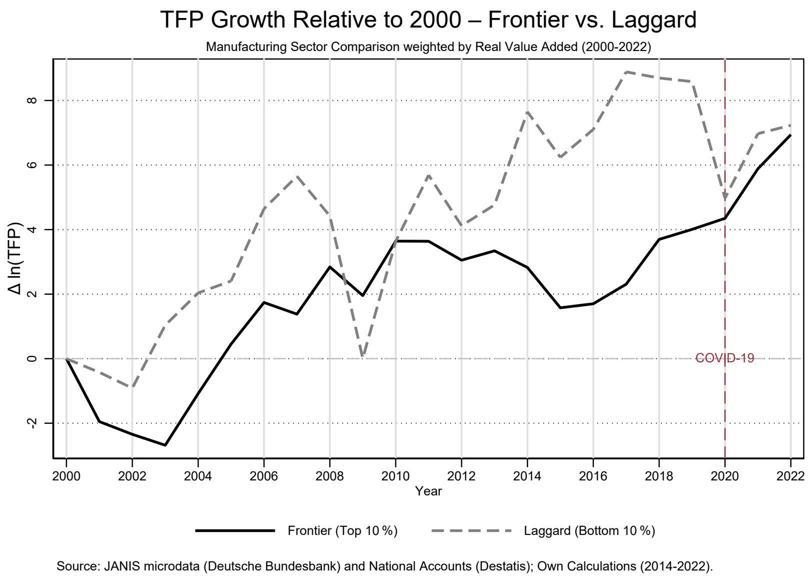


Figure C.24: TFPQ of Frontier vs. Laggard Firms in German Manufacturing (relative to 2000). Source: JANIS microdata (Deutsche Bundesbank) and VGR (Destatis). Own calculations.

C.2 Winsorizing

This section reports robustness checks for the choice of winsorizing thresholds in the Hsieh–Klenow analysis. While the main results are based on trimming extreme values of VA at the 1% and 99% percentiles, alternative specifications using 2%–98% and 5%–95% thresholds are implemented to ensure that the findings are not driven by a few extreme observations. The persistence of the main patterns across these alternative thresholds confirms that the baseline results are not an artefact of the chosen winsorization level for the same time period as in the main analysis (2014-2022).

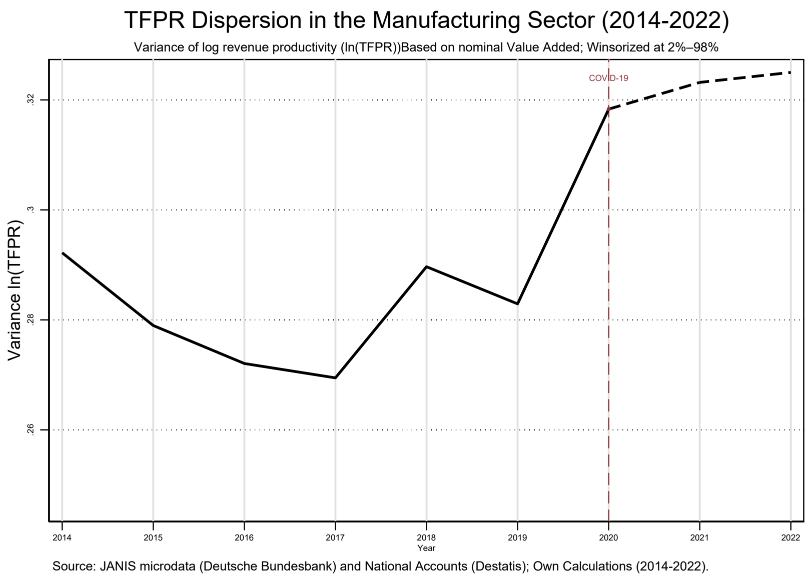


Figure C.25: Robustness check: TFPR dispersion in German manufacturing (nominal VA, winsorized at 2%–98%). Source: JANIS microdata (Deutsche Bundesbank) and VGR (Destatis). Own calculations.

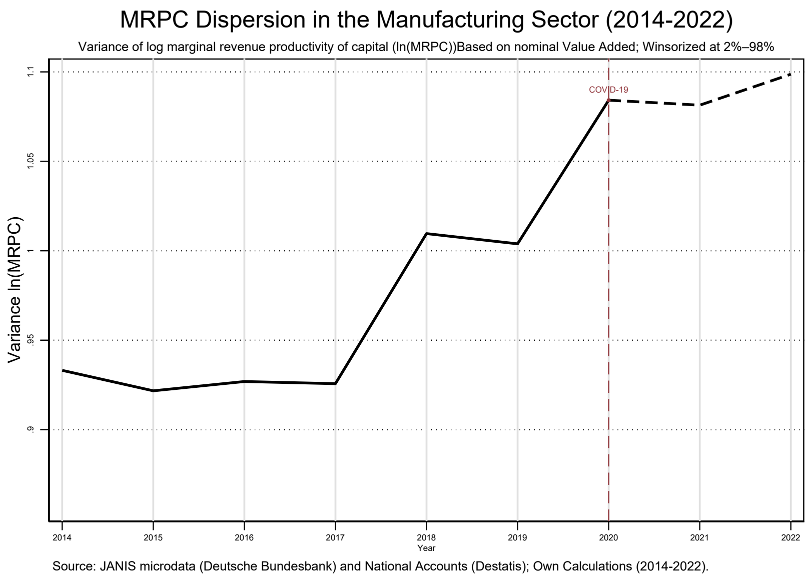


Figure C.26: Robustness check: MRPC dispersion in German manufacturing (nominal VA, winsorized at 2%–98%). Source: JANIS microdata (Deutsche Bundesbank) and VGR (Destatis). Own calculations.

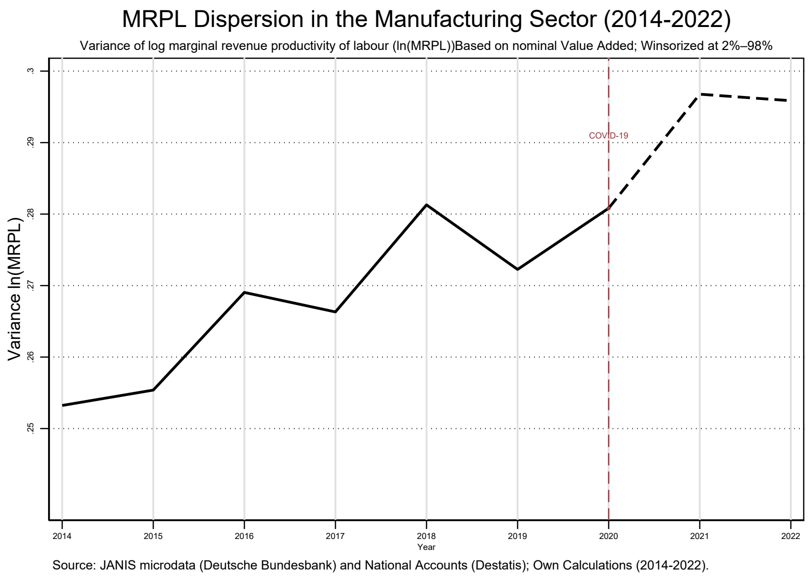


Figure C.27: Robustness check: MRPL dispersion in German manufacturing (nominal VA, winsorized at 2%–98%). Source: JANIS microdata (Deutsche Bundesbank) and VGR (Destatis). Own calculations.

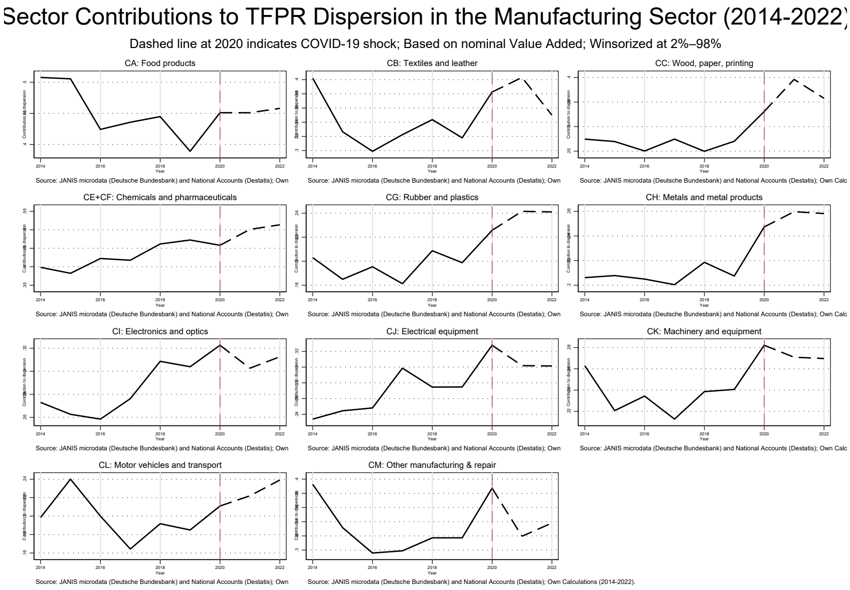


Figure C.28: Robustness check: Sectoral contributions to TFPR dispersion in German manufacturing (nominal VA, winsorized at 2%–98%). Source: JANIS microdata (Deutsche Bundesbank) and VGR (Destatis). Own calculations.

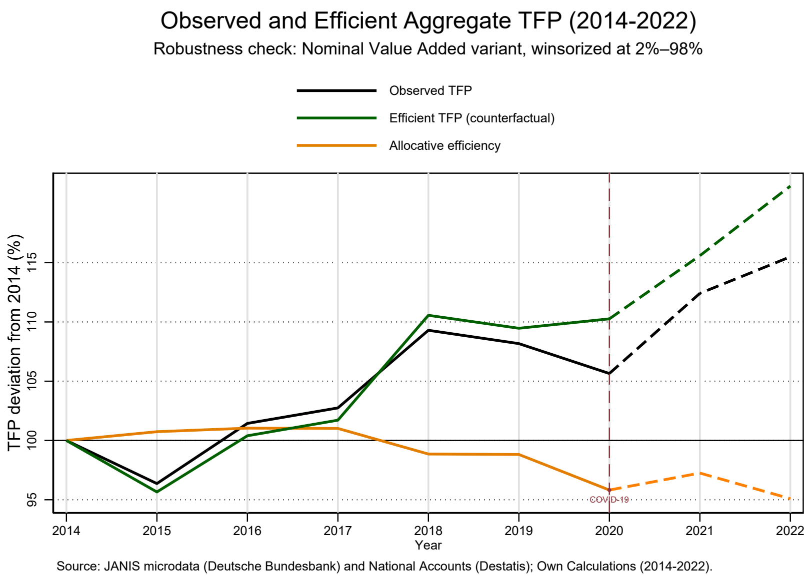


Figure C.29: Robustness check: Aggregate observed and efficient TFP in German manufacturing (nominal VA, winsorized at 2%–98%). Source: JANIS microdata (Deutsche Bundesbank) and VGR (Destatis). Own calculations.

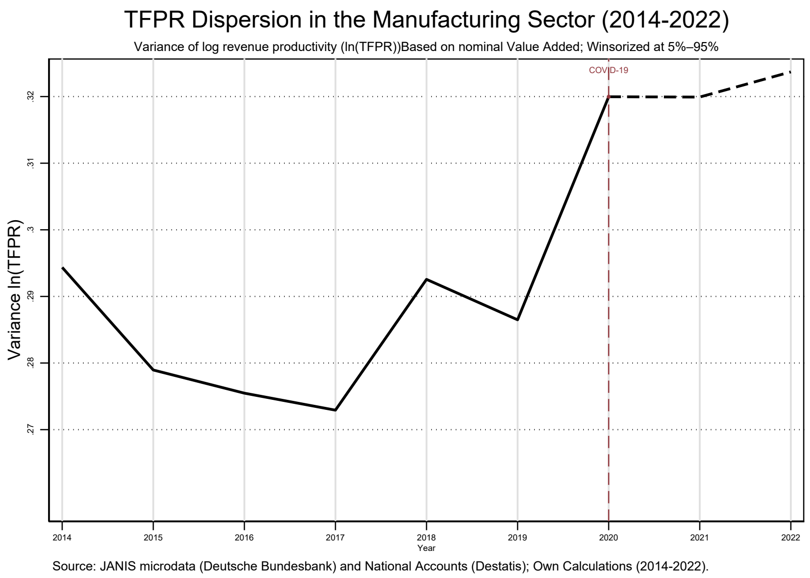


Figure C.30: Robustness check: TFPR dispersion in German manufacturing (nominal VA, winsorized at 5%–95%). Source: JANIS microdata (Deutsche Bundesbank) and VGR (Destatis). Own calculations.

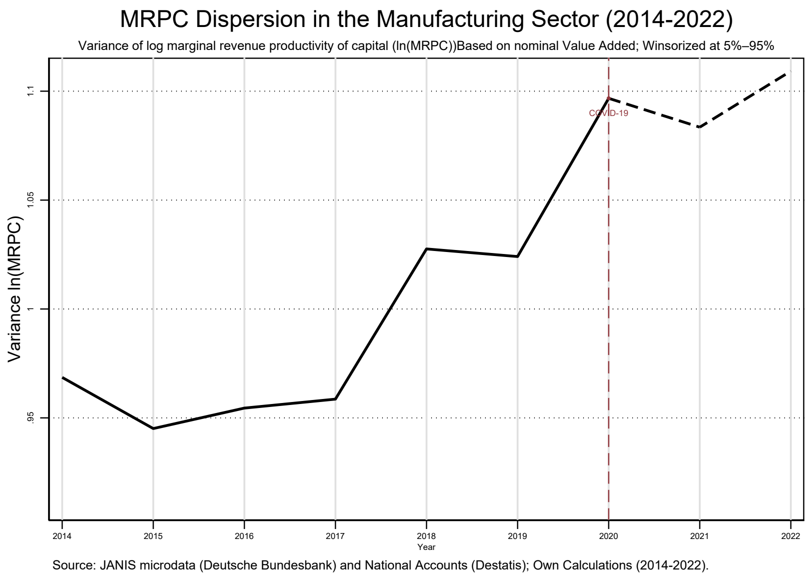


Figure C.31: Robustness check: MRPC dispersion in German manufacturing (nominal VA, winsorized at 5%–95%). Source: JANIS microdata (Deutsche Bundesbank) and VGR (Destatis). Own calculations.

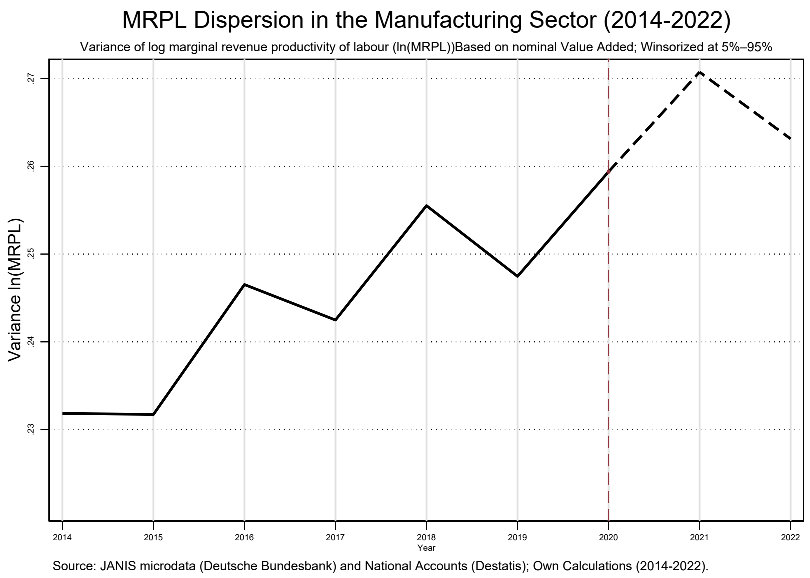


Figure C.32: Robustness check: MRPL dispersion in German manufacturing (nominal VA, winsorized at 5%–95%). Source: JANIS microdata (Deutsche Bundesbank) and VGR (Destatis). Own calculations.

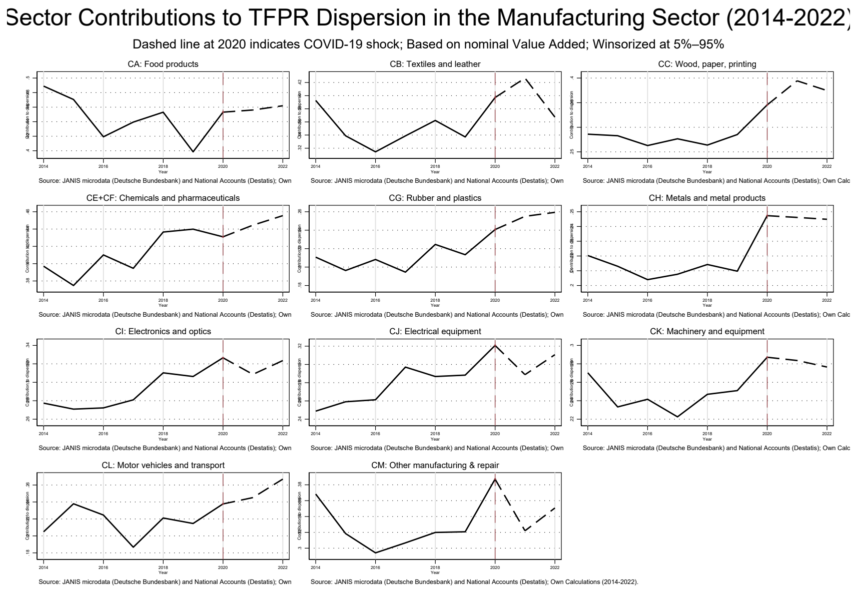


Figure C.33: Robustness check: Sectoral contributions to TFPR dispersion in German manufacturing (nominal VA, winsorized at 5%–95%). Source: JANIS microdata (Deutsche Bundesbank) and VGR (Destatis). Own calculations.

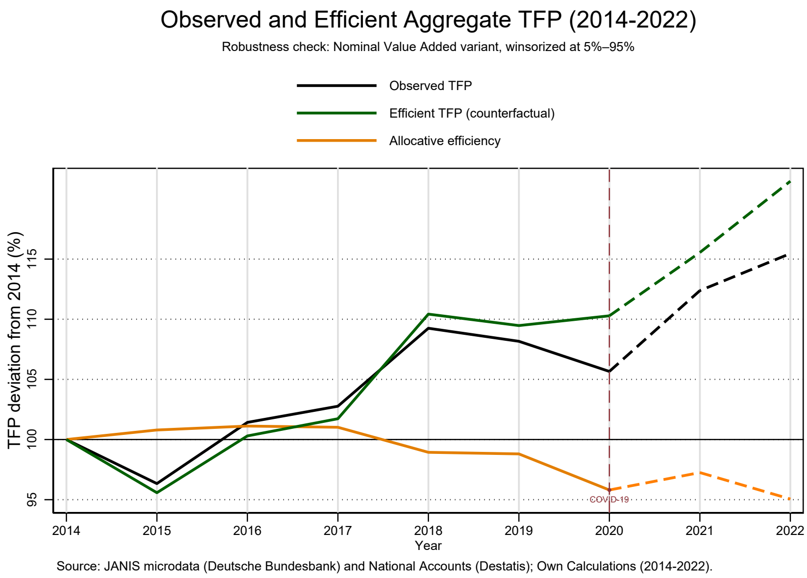


Figure C.34: Robustness check: Aggregate observed and efficient TFP in German manufacturing (nominal VA, winsorized at 5%–95%). Source: JANIS microdata (Deutsche Bundesbank) and VGR (Destatis). Own calculations.

C.3 H & K - Framework Total-Output Based

As an additional robustness check, I replicate the analysis using total output as base for VA instead of VA sales based as the basis for productivity and TFPR measurement for the same time period as in the main analysis (2014-2022). The sample is winsorized at the same threshold 1^{nd} and 99^{th} percentiles to ensure comparability with the baseline. Results remain qualitatively robust.

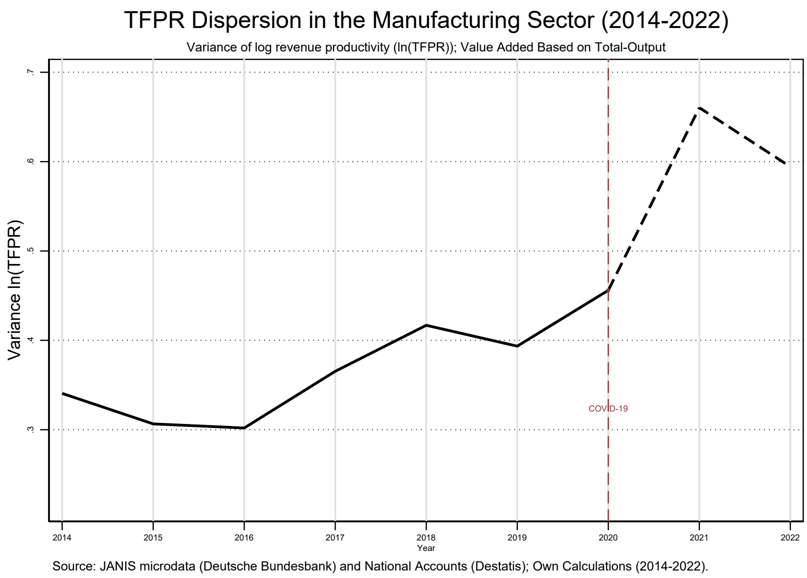


Figure C.35: Robustness check: TFPR dispersion in German manufacturing (VA, total-output based). Source: JANIS microdata (Deutsche Bundesbank) and VGR (Destatis). Own calculations.

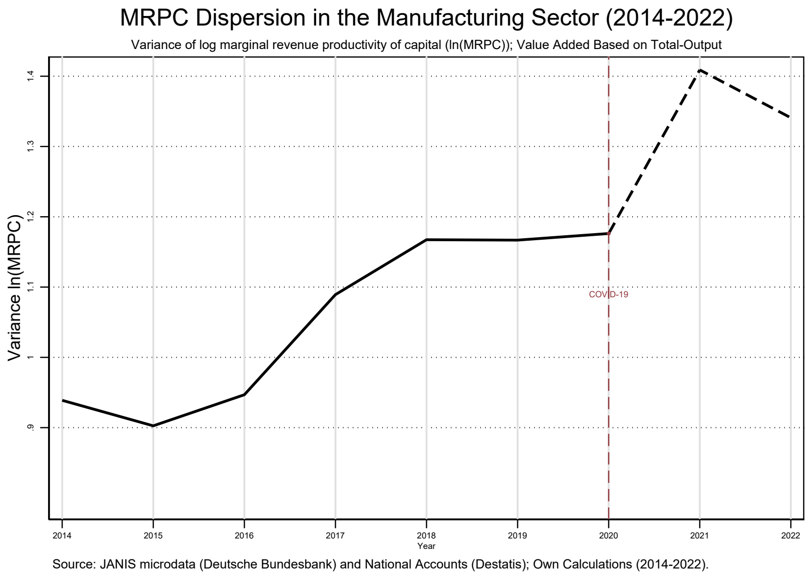


Figure C.36: Robustness check: MRPC dispersion in German manufacturing (VA, total-output based). Source: JANIS microdata (Deutsche Bundesbank) and VGR (Destatis). Own calculations.

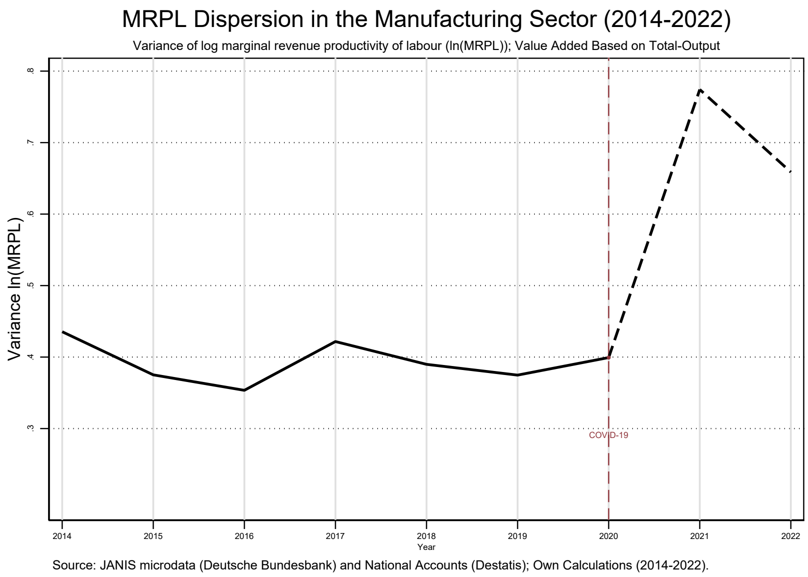


Figure C.37: Robustness check: MRPL dispersion in German manufacturing (VA, total-output based). Source: JANIS microdata (Deutsche Bundesbank) and VGR (Destatis). Own calculations.

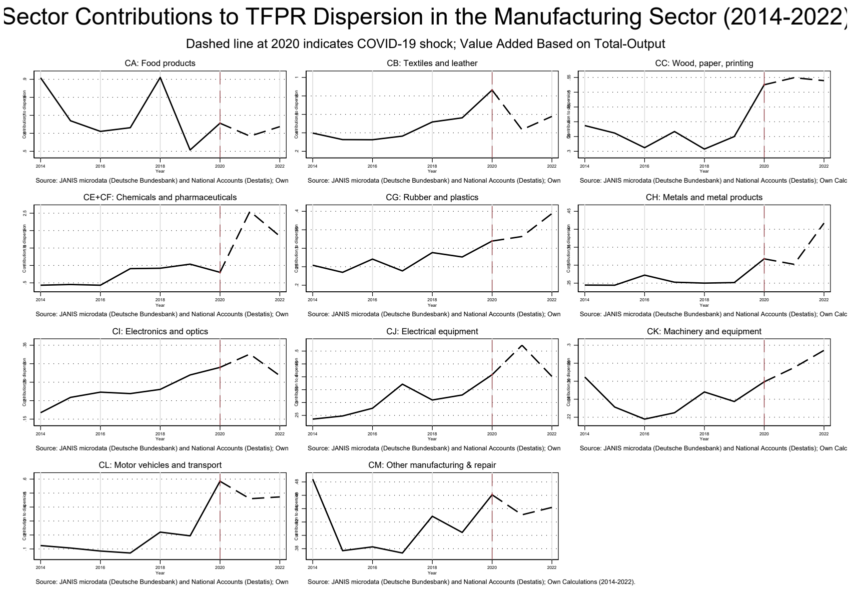


Figure C.38: Robustness check: Sectoral contributions to TFPR dispersion in German manufacturing (VA, total-output based). Source: JANIS microdata (Deutsche Bundesbank) and VGR (Destatis). Own calculations.

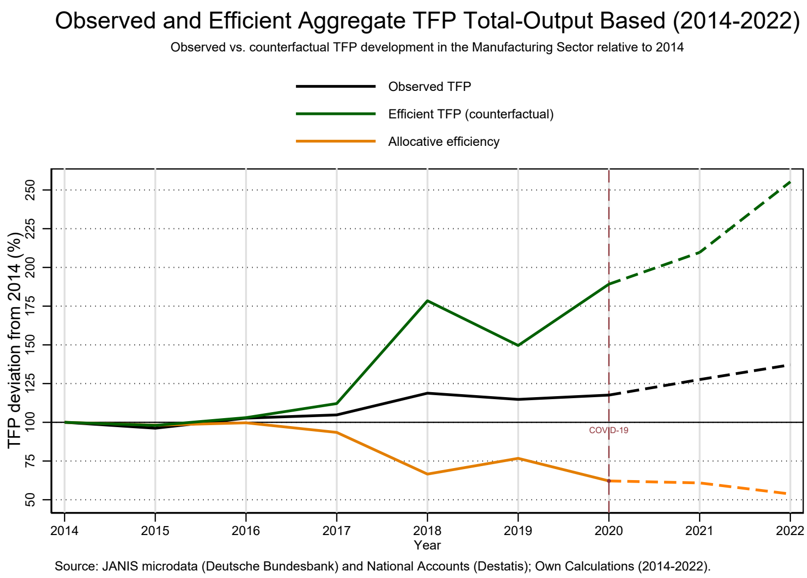


Figure C.39: Robustness check: Aggregate observed and efficient TFP in German manufacturing (VA, total-output based). Source: JANIS microdata (Deutsche Bundesbank) and VGR (Destatis). Own calculations.

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EXECUTIVE SUMMARY

This thesis investigates the development and determinants of allocative efficiency in the German manufacturing sector from 2014 to 2022. The primary objective is to quantify the extent and dynamics of factor misallocation and assess its consequences for productivity. To achieve this, harmonized firm-level data from the JANIS microdata panel of the Deutsche Bundesbank are combined with national accounts from the German Federal Office of Statistics.

The analysis employs three complementary approaches: the misallocation framework of Hsieh & Klenow (2009), the Olley–Pakes (1996) decomposition, and input-specific markup estimation following Raval (2023). The results demonstrate a marked increase in revenue-based total factor productivity (TFP) dispersion—particularly for the marginal revenue product of capital and labour—since 2017, with a sharp spike during the COVID-19 pandemic.

Concurrently, the correlation between firm productivity and market share has weakened, signaling a decline in the effectiveness of reallocative productivity gains. Input-specific markup estimates further indicate that the pandemic has distorted not only capital markets but also labour and material markets.

These findings underscore the need for targeted economic policy measures to reduce input-specific misallocation and to strengthen the reallocation of productive resources. Overall, the thesis contributes empirical evidence to the literature on misallocation and informs the ongoing debate on evidence-based industrial policy in Germany, that there is indeed a lost productivity potential.

MOTS-CLÉS/KEYWORDS: Productivity, Misallocation, Firm-Level Data, Germany, Capital Distortions, Labor Market Rigidities, TFPR, Sectoral Analysis (D24, E23, L11, O47)

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