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Allocative Efficiency, Plant Dynamics and Regional Productivity: Evidence from Germany

Simon Bruhn* and Thomas Grebel†

Abstract: This paper argues that regional variation in the efficiency of labor allocation among German manufacturing plants plays a critical role in explaining regional disparities in productivity. In fact, we show that over 50% of the East-West productivity gap is associated with a less efficient labor allocation in former East Germany. Yet, we also demonstrate that the mere focus on East-West comparisons hides partially large differences between the German federal states. These results suggest that regional productivity differences could be substantially narrowed by a more efficient labor allocation among plants. With respect to the underlying causes, we find evidence that the regional differences in allocative efficiency are significantly correlated with differences in export intensity, market concentration and plant size.

Keywords: Regional productivity gap, productivity decomposition, allocative efficiency, labor allocation

JEL classification: E24, J24, L11, L25, O47

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1 Introduction

Productivity growth is vital for the general improvement of real incomes and living standards (Schreyer and Pilat, 2001). Achieving equal living standards and opportunities across Germany is a central socio-political goal of the German government, which is also institutionally reflected in the commission for 'equal living conditions', founded in 2018 (see e.g., Röhl, 2020). Given this goal, and due to the close link between productivity and living conditions, reducing the consistently large productivity disparities in German regions and between East and West constitutes one of the major challenges for German policy makers. Given the importance of this objective, it is unsurprising that there is abundant literature regarding possible reasons for the productivity differences and how to overcome them (see e.g., Niebuhr, 2000; Eckey et al., 2007; Brunow and Hirte, 2009; Görzig et al., 2010; Belitz et al., 2020).

What has so far not been addressed by the literature is the role of allocative efficiency in explaining these regional productivity differences. In other words, to what extent can the observed aggregate productivity differences be attributed to actual firm- or plant-level productivity differences, and to what extent are they caused by differences in the efficiency in resource allocation among these establishments? Distinguishing between and quantifying these components of aggregate productivity can provide a more detailed understanding of the productivity differences and how best to address them. As shown by a considerable number of studies, ignoring the impact of resource allocation on aggregate productivity developments would mean ignoring a crucial driver of productivity growth.

In our study, we investigate the role of allocative efficiency for regional labor productivity in Germany, using the decomposition method by Olley and Pakes (1996). We focus on the manufacturing sector, using the official dataset on German manufacturing plants from 2004 to 2018 by the German statistical office (AFiD panel). Our results are threefold. First, we show that East-West as well as regional productivity disparities can be significantly attributed to differences in allocative efficiency. In fact, we find that over 50% of the gap between aggregate productivity in East and West Germany can be explained by the less efficient labor allocation among plants. Second, we detect a general decline in allocative efficiency between 2004 and 2018, which is more pronounced for East German states. This results in a further widening of the observed discrepancies in allocative efficiency. Third, we show empirically that the regional disparities are significantly related to differences in export intensity, market concentration and plant size.

Our paper generally contributes to two different strands of literature. First, it contributes to the literature on the relationship between resource allocation and productivity, providing new evidence with respect to the less investigated *regional* impact of allocative efficiency, while delivering new insights into how the observed patterns in allocative efficiency are associated with regional industry characteristics. Second, our paper contributes to the broad range of empirical literature on the determinants of productivity differences in Germany. Even though our results reveal important insights regarding East-West differences, they simultaneously indicate that the focus on East-West comparisons hides partially large regional differences. The knowledge of these regional discrepancies may be of particular importance for deriving policy implications tailored to the needs of the individual states.

The remainder of this paper is structured as follows. In Section 2, we emphasize our hypothesis that allocative efficiency plays a major role in explaining regional productivity disparities in Germany. Section 3 presents the data used. In Section 4, we lay out the decomposition method deployed in our analysis. Section 5 offers a descriptive analysis of allocative efficiency and labor productivity in German regions. In Section 6, we perform an econometric analysis substantiating the productivity potential of a reallocation of employees and derive policy implications on how to narrow the regional discrepancies in allocative efficiency. Section 7 concludes.

2 Why allocative efficiency matters for regional productivity differences in Germany

It is a central objective of policy makers to reduce regional productivity differences. Various empirical studies show that such regional disparities are prevalent in Germany. One group of studies, for instance, investigates productivity convergence in German regions and its underlying forces. They identify spatial differences in technology spillovers or infrastructure to explain (the lack of) convergence (see e.g., Niebuhr, 2000; Eckey et al., 2007). Others provide a more general view on the determinants of regional productivity differences in Germany, studying aspects such as differences in human capital, capital intensity, product policy, or firm size (Brunow and Hirte, 2009; Görzig et al., 2010; Belitz et al., 2020).

All these studies contribute to explaining how firm productivity evolves and why firms differ in productivity. Yet, whether input factors, such as labor, are allocated efficiently across firms with different productivity levels, and how this affects regional productivity, has so far not been addressed by the literature. In fact, we know very little concerning the extent to which regional productivity differences can be attributed to differences in firm productivity or to what extent they are caused by differences in the efficiency of resource allocation between firms. Distinguishing allocative efficiency from firm-level productivity will enhance our understanding of regional productivity differences and help narrow down the search for the underlying reasons.

The importance of the (re)allocation of resources between firms has been widely documented in the literature. By now, it is well established that, even within narrowly defined industries, firm-level productivity is highly dispersed (see e.g., Bartelsman et al., 2013; Dosi et al., 2021). There is a considerable body of literature using micro-level data to show the prevalence of resource reallocation processes between heterogeneous firms, typically by using so-called productivity decomposition methods (see e.g., Baily et al., 1992; Griliches and Regev, 1995; Olley and Pakes, 1996; Foster et al., 2001; Disney et al., 2003; Bartelsman et al., 2013; Decker et al., 2017; Brown et al., 2018). With respect to the impact of resource allocation on *regional* productivity, the number of studies is rather limited. Still, it is evident from these studies that the allocation and reallocation of market shares between firms and industries are key drivers of regional productivity developments. For example, Rigby and Essletzbichler (2000) show large discrepancies among states within the U.S. regarding the impact of resource reallocation on productivity growth, while Le Gallo and Kamarianakis (2011) perform a similar analysis on regions within the European Union. Moreover, Böckerman and Maliranta (2007) conduct a decomposition study on Finnish regions, revealing significant differences in resource allocation among firms with different levels of productivity.

Taking a stance similar to these studies, we investigate the role of allocative efficiency in explaining regional productivity differences in Germany. Based on the findings of previous work, we expect to see large differences in allocative efficiency with a significant impact on regional productivity. A potential driver of regional differences particular to Germany lies in the former division until 1990 into East and West. The market economy in West Germany and the planned economy in East Germany rested on very different mechanisms for (re)allocating resources among companies. Hence, it is conceivable that the footprint of these two different economic systems is still visible today.

Apart from showing the high relevance of allocative efficiency for regional productivity differences, we aim to explain why we observe regional variations in allocative efficiency. The list of potential drivers of firm productivity dispersion and allocative efficiency is long. According to Foster et al. (2001), essential drivers of firm-level heterogeneity include the uncertainty of the business environment, plant-level differences (such as managerial ability, capital vintage, location, and disturbances) and the diffusion of knowledge among firms. With respect to the drivers of reallocation processes, Melitz (2003) shows that trade exposure fosters reallocation, as only the most productive firms self-select and benefit from trade. Moreover, he argues that trade exposure makes it more difficult for less productive firms to be profitable, which causes them to exit the market. Similarly, Syverson (2011) argues that an increase in competition both from domestic and foreign competition reinforces the market selection process. As a further driver, he emphasizes that flexible input markets (labor and capital) facilitate the reallocation of resources towards their most productive uses. In a more recent study, Brown et al. (2018) demonstrate that product market, education, and financial market reforms play an important role in the dynamics of resource allocation. Our hypothesis is that these explanatory factors differ not only between industries or countries, but also between regions within the same country. Therefore, we investigate whether the mentioned drivers, given data is available, can be associated with regional allocative efficiency in Germany. This exercise can be a first step towards deriving specific policies that can narrow regional disparities in productivity.

3 Data

Our analysis is based on an official dataset of German manufacturing plants covering the period from 2004 to 2018. The data is provided by the German statistical office (AFiD panel).[1] We deliberately rely on plant-level rather than firm-level data as it better reflects the regional manufacturing landscape, given that many large firms have plant subsidiaries in different German regions that would not appear in a firm-level database which only registers firms' headquarters (Leibnitz IWH, 2019). Moreover, using plants instead of firms almost triples the number of establishments that we can use for our decomposition analysis which allows us to cover more sectors and regions and provide a more comprehensive picture of the manufacturing industry.

[1]Source: RDC of the Federal Statistical Office and Statistical Offices of the Länder, "AFiD-Panel Industriebetriebe", 2004-2018, own calculations.

To construct our productivity measure, we use the number of employees as our input and sales as our output measure. Because we do not observe prices, we deflate plant-level sales using industry specific gross output deflators from the Eurostat database on national accounts aggregates. The plant-level dataset does not provide information on value-added which would take the use of intermediate goods into consideration and would thus represent the more accurate output measure when comparing plants with different production processes. However, previous studies have shown that there is a high correlation between value-added and gross output within narrowly defined industries, as the pattern of intermediate goods is similar within the same industry (see e.g., Foster et al., 2001; Bartelsman et al., 2013).

With respect to the industry classification chosen for our analysis, we faced a trade-off between the reliability of decomposition results, mostly determined by the granularity of the industry classification and the number of plants per industry, and the desire to provide an all-encompassing analysis by covering as many manufacturing plants as possible. We therefore decided to set the minimum number of plants per sector at 20 plants and used the intermediate SNA/ISIC aggregation A38 as industry classification, which aggregates similar ISIC two-digit divisions to 13 sectors (Eurostat, 2008).[2] The list of industries included in our dataset can be found in Table A1 in Appendix A. Even though a more granular industry classification would improve the comparability between plants, it would also imply losing a large part of manufacturing plants given the constraints in the dataset.[3] Except for the states of Bremen and Saarland, our choice for the industry classification and the minimum number of plants allows us to cover six intermediate sectors in each state and year, comprising 14 out of the 24 ISIC two-digit manufacturing industries. With these 14 ISIC divisions in each of the 14 states, our analysis includes an annual number of more than 30,000 plants, which equals around 75% of all plants registered in the plant-level database provided by the German statistical office. Table 1 reports summary statistics of the sample.

As shown in Table 1, we focus on three different periods: 2004-2006, 2010-2012, and 2016-2018. This allows us to not only compare allocative efficiency and productivity between different states within each of these periods but also to track their development over a long time span. Moreover, the selected periods enable us to cover the time just before the Great Recession from 2007 to 2009 and compare it to the subsequent periods to investigate potential changes caused by the disruption. To reduce the impact of extreme values, we truncated the data for each industry and year at the 1st and 99th percentile of productivity and eliminated plants with suspiciously large changes in productivity from one year to another (namely, we used the factor 3).

[2]For data reported after 2008, the German statistical office implemented a change in the industry classification from WZ 2003 to WZ 2008 (ISIC Rev. 3.1 to ISIC Rev. 4) to adjust to developments in the economic structure. To facilitate comparisons between the periods before and after this adjustment, we use the conversion tables published by Dierks et al. (2020).

[3]In fact, when choosing the more granular classification of ISIC two-digit industries, the restriction of 20 plants per industry and state only leaves three ISIC two-digit industries and covers less than half of the manufacturing plants registered in the database. Still, as a robustness check, we conducted our decomposition analysis for these three industries. We observe no significant change in the key patterns between states which we derived for the intermediate industry classification. Furthermore, in addition to our state-level analysis, we also conducted the OP decomposition for East and West Germany as a whole. Given the restriction of 20 plants per industry, this leaves 20 two-digit industries in East and West. The results corroborate the findings we draw from our state-level analysis regarding differences between East and West.

Table 1: Summary statistics for German manufacturing plants between 2004 and 2018

	Count	Mean	SD	p5	p95
2004-2006					
Sales	92,042	19,743.8	65,762.6	1,003.7	75,249.1
Employment	92,042	98.6	212.4	12.4	334.2
Labor Productivity	92,042	162.5	142.8	40.7	404.5
2010-2012					
Sales	91,410	21,211.9	77,770.6	1,103.1	80,655.3
Employment	91,410	104.3	245.6	14.0	345.5
Labor Productivity	91,410	166.4	156.6	41.5	427.3
2016-2018					
Sales	95,199	22,017.6	75,891.8	1,184.1	84,548.2
Employment	95,199	108.8	254.3	15.0	364.6
Labor Productivity	95,199	167.7	153.9	42.6	423.5

Notes: The table depicts summary statistics for plants within the manufacturing sector during the three time periods considered in our study. All values are reported for the cleaned sample as documented in Section 3. Sales are reported in thousand deflated euros, productivity is measured in thousand deflated euros in sales per employee. SD is the standard deviation, p5 and p95 describe the 5th and 95th percentile of the distribution, respectively.

The data provided by the German statistical office is an unbalanced panel with new plants entering and incumbents exiting the database. Unfortunately, the German data does not reliably distinguish 'real' entries and exits from events with no consequences for industry churning, such as changes in ownership or name, changes in the plant or firm ID or simple gaps in reporting. This is a common issue of many micro-level databases (Haltiwanger et al., 2013). It is, in particular, a problem with respect to a decomposition study that aims at shedding light on industry dynamics, of which entries and exits make up a considerable part. One option to deal with this lack of information would be to simply drop all entries and exits and to consider only those plants that are constantly in the market, thereby creating a balanced panel of plants that can be consistently tracked over time. However, for the purposes of our study, this is not a viable option because we would lose a substantial part of plants and could thus make only very limited statements regarding the state of the manufacturing sector in German regions. We, therefore, conduct our analysis using the unbalanced panel and address the lack of plant traceability by applying the cross-sectional decomposition method by Olley and Pakes (1996) instead of a time-series approach.

4 Methodology

4.1 Productivity decomposition by Olley and Pakes (1996)

For our empirical analysis, we use the productivity decomposition method proposed by Olley and Pakes (1996) (OP). It is a widely applied tool to measure the contribution of resource allocation among firms to aggregate productivity (see e.g., Bartelsman et al., 2004, 2009, 2013; Maliranta and Määttänen, 2015; Hyytinen et al., 2016; Brown et al., 2018). In contrast to the various 'dynamic' time-series approaches in the literature which investigate productivity *growth* (Griliches and Regev, 1995; Foster et al., 2001; Melitz and Polanec, 2015), the OP method follows a cross-sectional logic and provides a picture of the state of allocative efficiency in an industry or economy at a given point in time. It may, therefore, be considered a 'static' productivity decomposition (Brown et al., 2018).

The starting point for the decomposition method proposed by Olley and Pakes (1996) is the definition of aggregate productivity as a share-weighted sum of plant-level productivity:

$$P_t = \sum_i s_{it} p_{it} \tag{1}$$

where p_{it} denotes the productivity level and s_{it} the share of plant i at time t. As explained in Section 3, we use sales per employee as our productivity measure. For input shares, we use the number of employees relative to the industry aggregate within the respective federal state. Contrary to the common practice in decomposition studies to measure productivity in logs, we represent productivity in levels due to the potential pitfalls associated with using logs, as pointed out by Dias and Marques (2021) and Bruhn et al. (2021).

The OP decomposition method decomposes aggregate productivity into two components which we term a within-plant and a between-plant component. The within-plant component is represented by the unweighted mean of plant-level productivity, whereas the between-plant component is expressed by the covariance between plant productivity and input share:

$$\begin{aligned} P_t &= \overline{p}_t + \sum_i (s_{it} - \overline{s}_t)(p_{it} - \overline{p}_t) \\ &= \overline{p}_t + \mathrm{cov}(s_{it}, p_{it}) \end{aligned} \tag{2}$$

with $\overline{p}_t$ and $\overline{s}_t$ representing unweighted means. We follow the 'abuse of notation' for the cov operator suggested by Melitz and Polanec (2015), omitting the division of the sum by the number of firms as this is already included in the market shares.

It follows from the above equation that the covariance term represents the gap between the unweighted and the weighted mean of plant-level productivity. To make this gap comparable across years, states and industries, we present it as a share of the corresponding aggregate industry productivity, that is, $\mathrm{cov}(s_{it}, p_{it})/P_t$. This share can be interpreted as the part of aggregate productivity that is explained by the efficient allocation of resources among plants. In other words, it is a measure for the market's capability of channeling resources away from the less and towards the more productive plants. Consequently, one can generally interpret an increase in the share of the covariance term as a more efficient allocation of employees across plants. It is the magnitude and development of this covariance share which we will focus on in our analyses in Sections 5 and 6.

Despite its practical usefulness and wide-spread application, we want to briefly reflect on some caveats of the Olley-Pakes decomposition.

As we deal with an unbalanced panel of plants, the development of the covariance term may be strongly affected by entering and exiting plants that typically play an important role in shaping industry dynamics. Hence, as stated in Section 3, even though our dataset does not allow to clearly identify entries and exits, it is a crucial advantage of the OP method that these plants' impact on resource allocation is reflected in the measure of allocative efficiency (see e.g., Olley and Pakes, 1996; Schneider, 2018). However, as pointed out by Brown et al. (2018), in the presence of exits, the interpretation of changes in the covariance term as a measure of allocative efficiency is not always straightforward. As follows from Equation (2), a plant with both below-average productivity and market share will contribute positively to the covariance term. This is in line with the intuition of the efficiency measure because it implies that comparatively few resources are tied to an unproductive plant. However, if this unproductive plant exits the market, the covariance term may be negatively affected, even though an efficient market is supposed to eventually push unproductive plants out of the market.[4] In this case, it is questionable whether to consider the plant's exit as a decrease in allocative efficiency. Nonetheless, this effect can be assumed to be present in all states and industries so that we do not expect this 'mismeasurement' to pose an issue in the state- and industry-level comparisons in sections 5 and 6.

A further caveat arises with respect to the interpretation of how changes in the covariance term affect productivity growth. As follows from Equation (2), an increase in the covariance term will, ceteris paribus, lead to an increase in aggregate productivity. However, this is a simplification, as a change in allocative efficiency may entail changes in the productivity levels of plants, which, in turn, affect aggregate productivity. In fact, aggregate productivity might even decrease in spite of an increase in allocative efficiency for which there are two reasons.

The first reason simply follows from the way the OP decomposition measures allocative efficiency. As shown in Equation (2), an increase in allocative efficiency may occur because a plant with below-average market share decreases its productivity. Ceteris paribus, the overall effect on aggregate productivity will always be negative, even though allocative efficiency has increased. In the presence of entries and exits, similar scenarios are possible. For instance, if a firm enters with below-average productivity and share, this can lead to an increase in the covariance term, while reducing aggregate productivity. It is also conceivable that the entry of a firm with above-average productivity but below-average market share increases aggregate productivity but decreases allocative efficiency. Consequently, the opposite effects on productivity and allocative efficiency would occur if such firms exited the market.

The second reason follows from an implicit assumption commonly made in productivity decomposition. When quantifying the contribution of resource allocation to productivity, decomposition studies typically assume constant returns to scale. Put differently, it is assumed that plants' productivity level stay constant when they expand or contract in size. Yet, this need not be the case. To clarify, suppose that a plant with above-average productivity increases its market share by hiring more workers, which contributes positively to allocative efficiency. Let us further assume that these additional workers will not be as productive as the workers already employed at this plant. This lowers the plant's productivity which, in turn, contributes negatively to the covariance term and the unweighted average productivity within the industry. Even though the covariance term may still increase because the increased market share overcom-

[4] This firm's exit can, in fact, also positively affect the covariance term, depending on how this firm's exit affects the average productivity and the average market share, and thereby all other firms' contributions to the covariance term.

pensates the decreased productivity, the decrease in the unweighted average productivity may lower aggregate productivity more strongly than the positive impact of the increase in allocative efficiency.

In short, the relationship between aggregate labor productivity and allocative efficiency is more ambiguous as it may appear at first sight. As shown, it is possible that an increase in allocative efficiency will come at the cost of a decrease in productivity. If this were the case in our sample, the suggestion of policy implications that would increase allocative efficiency would be counterproductive. Therefore, we empirically show in Section 6 that, in our sample, an increase in allocative efficiency entails an increase in aggregate productivity.

4.2 Decomposing aggregate productivity on the industry-state level

For our analysis of allocative efficiency in the German federal states, we apply Equation (2) annually on the industry-state level, that is, we compute allocative efficiency within each industry for each state individually. Hence, we compute plant-level shares, s_{it}, as the ratio between the size of an individual plant (in employees) and the size of the industry within the respective state where this plant is situated.

Measuring allocative efficiency *within* industries is common in the literature (see e.g., Bartelsman et al., 2013; Brown et al., 2018). It assumes that intra-industry competition and labor movements dominate cross-industry effects. The assumption that intra-industry competition dominates simply follows from the similarity in the goods and services produced by these plants. For labor movements, the assumption is that plants of the same industry have similar requirements with respect to employees' qualifications which facilitates their mobility across plants.

We compute the within-industry measure for each state individually to enable a comparison between the German federal states. In doing so, we aim to understand whether some states are more efficient than others in reallocating employees towards the most productive plants in their region. This, however, implies that we assume each state and the comprising industries to constitute a somewhat isolated unit. Evidently, most manufacturing plants in Germany can be expected to compete on a Germany-wide or even global scale. Moreover, workers can move between different states, in particular those situated near to inner German state borders. This cross-border competition and worker movement affects allocative efficiency in all states. Even though this represents an important limitation of our measure, we expect these cross-border effects to be less important for state-level allocative efficiency than within-state effects. In particular, we assume that labor reallocation will primarily occur within state boundaries.

To facilitate cross-state comparisons, we aggregate the annual industry-state level results for allocative efficiency to a weighted average industry for each state and year. Following the example of Bartelsman et al. (2013), we aggregate the annual industry-level results using state- and time-invariant industry employment as weights. More precisely, we use Germany-wide employment per industry as weights for the individual industries, averaged over the whole time period.[5] By using state- and time-invariant shares, we remove the impact of state-individual

[5] We also computed the weighted average industry using time- and state-individual weights instead. The main conclusions drawn from our analysis stay the same.

industry compositions and changes thereof. In other words, we control for the fact that, for instance, a highly productive industry could be large in one specific state, but small in the other states, which would impair our objective of drawing cross-state comparisons of allocative efficiency *within* industries.

5 Allocative efficiency and regional productivity in Germany

In this section, we investigate the development of allocative efficiency and regional labor productivity in Germany, using the decomposition method by Olley and Pakes (1996) and the procedure explained in Section 4.2. We analyze the level and the development of allocative efficiency and productivity across three time periods, namely across the periods 2004-2006, 2010-2012 and 2016-2018. Because our focus lies on the analysis of more long-term trends in allocative efficiency and productivity rather than annual changes, we computed averages of the annual covariance terms and productivity values for each period.

We begin our analysis by outlining the development of allocative efficiency and labor productivity in Germany. Subsequently, we will shed light on the differences between former East and West Germany before we turn to the comparison of the federal states. As stated above, our analysis is focused on the manufacturing sector as a whole. Note that we observe substantial heterogeneity in productivity and allocative efficiency across industries. We report the according distributions in Appendix B. The high degree of heterogeneity implies that some of our conclusions and implications derived from our analysis may apply more to one industry than the other. Still, by using identical industry weights for each state (see Section 4.2), we reduce the possibility that industry-specific values distort the general patterns we identified in these comparisons.

5.1 Allocative efficiency and labor productivity in East and West Germany

As shown in Table 2, allocative efficiency in Germany has experienced a notable and steady decrease from initially 17.8% in the 2004-2006 period to 15.8% between 2016 and 2018. Labor productivity, in turn, has undergone only minor changes, hovering at a level of roughly 200,000 euros in sales per employee. Because allocative efficiency has decreased, this roughly constant aggregate labor productivity implies that the unweighted average of plant-level productivity has increased, compensating the less efficient distribution of labor.

When dividing the overall values into the parts of former East and West Germany, a clear gap becomes apparent, with the West exceeding the East both in allocative efficiency as well as in labor productivity. A very similar pattern appears when excluding Berlin in the comparison (see Table 2). While the East-West productivity gap was to be expected, its concurrency with a gap in allocative efficiency has so far, to the best of our knowledge, not been documented in the literature. This gap is even increasing over the three periods under investigation. Whereas East German allocative efficiency was still at roughly 82% of the West German level between 2004 and 2006, it was only at about 64% in the last period from 2016 to 2018. The reason for this widening gap is that the overall decline in allocative efficiency is significantly more pronounced

Table 2: Allocative efficiency and labor productivity in East and West Germany

	Allocative efficiency			Labor productivity		
	2004-2006	2010-2012	2016-2018	2004-2006	2010-2012	2016-2018
Germany	17.8	17.0	15.8	197.5	200.6	199.2
Former West Germany	18.3	17.8	16.6	202.3	204.9	202.7
Former East Germany	15.0	12.2	10.6	167.3	175.2	177.3
Former East ex Berlin	14.3	12.2	10.4	163.1	171.7	174.7

Notes: The table depicts average allocative efficiency (in percent of aggregate productivity) and labor productivity (in thousand deflated euros in sales per employee) for the three time periods. The values for each of the four regional boundaries listed in the left column are employment-weighted averages of the respective state-level results.

for East Germany, decreasing by about 30% from the first to the last period, compared to only a 10% decrease in the West.

In contrast to the decline in allocative efficiency, we do not observe a decrease in labor productivity. In East Germany, labor productivity even notably increased between the first and the last period by about 6%, in spite of the sharp decrease in allocative efficiency, while productivity in West Germany has remained more or less constant, showing a minor increase of only 0.2%. Hence, the overall slump in the efficiency of resource allocation is evidently compensated by an increase in average plant-level productivity, especially in East Germany. This significant productivity improvement in East Germany also becomes manifest in a notable narrowing of the East-West productivity gap over the periods under investigation. While, between 2004 and 2006, the West's productivity was around 21% larger relative to East German productivity, this gap shrank to only 14% in the 2016-2018 period.

Even though this already reveals a considerable catching-up process, the convergence in productivity could be significantly more advanced if allocative efficiency in East Germany had not experienced such a substantial deterioration. In fact, if we control for the gap in allocative efficiency between East and West in the 2016-2018 period by comparing their unweighted averages of plant-level productivity (158.4 and 169.0, respectively), the actual productivity gap of 14% is more than halved to less than 7%. In other words, over 50% of the 2016-2018 gap between aggregate productivity in East and West Germany are associated with a less efficient labor allocation among plants.

In sum, our results clearly indicate that the East-West productivity differences in manufacturing can be significantly attributed to disparities in the efficiency of labor allocation among plants. The market selection process that steers employees from the least towards the most productive firms appears to work in a considerably less efficient way in East than in West Germany. Moreover, we have identified a general decline in allocative efficiency over the period under study that is more pronounced in the East, which further increases the East's deficit in allocative efficiency. Lastly, we have shown that both closing the East-West gap in allocative efficiency as well as reversing the general decline in allocative efficiency offer large productivity potentials. In Section 6, we shed light on possible causes of the observed trends and derive policy implications on how to leverage this productivity potential.

5.2 Allocative efficiency and labor productivity in the German states

We now turn to the state-level results for allocative efficiency and productivity, which we report in Table 3. As explained in Section 3, we do not report any data for Bremen and Saarland due to their small number of plants. The former East German states comprise Brandenburg, Mecklenburg-West Pomerania, Saxony, Saxony-Anhalt, Thuringia and the Eastern part of Berlin. As can be seen from the table, there is substantial variation in allocative efficiency between states, ranging from a minimum of 4.2% in Mecklenburg-West Pomerania to as much as 24.7% in Rhineland-Palatinate. Apart from the variation between states, we also observe some considerable changes in allocative efficiency within states over the three periods. In analogy to our findings for the East-West comparison, these changes in allocative efficiency mostly follow a negative trend. While there are some notable exceptions in West German states, the decline in allocative efficiency includes all East German states and is particularly pronounced in Berlin, Brandenburg and Mecklenburg-West Pomerania. These three states experience a notable slump in allocative efficiency between the first two periods to roughly half their levels of the 2004-2006 period, mostly caused by a substantial decline in allocative efficiency in the industry of rubber, plastics and other non-metallic mineral products (ISIC 22-23). In Berlin and Mecklenburg-West Pomerania, we also observe a significant decrease in the industry comprising repair and installation of machinery and equipment as well as other manufacturing activities (ISIC 31-33), further explaining the steep fall in their allocative efficiency.

Despite these state-level variations over time, the general pattern with respect to the relatively more and less efficient states is mostly consistent over time. For example, the East German state of Mecklenburg-West Pomerania consistently shows the lowest values for allocative efficiency, ranging from 4.2% to 8.3%, while the efficiency is consistently highest in the Western state of Rhineland-Palatinate, varying between 22.6% and 24.7%. We visualized this rather time-consistent pattern between states as averages over the three time periods in Figure 1. In addition to underlining the considerable differences in allocative efficiency between states, it is clearly visible from Figure 1 that West German states tend to have a higher allocative efficiency than East German states. Hence, the gap in allocative efficiency between East and West Germany we have previously pointed out is supported also on the state level, that is, it is evidently not caused by single outliers on either side but applies to most of the constituent states.

This gap as well as the observed state-level variation are also reflected in the values for labor productivity, which are reported in Table 3 and visualized in Figure 2. In fact, comparing figures 1 and 2 shows that the more productive states also tend to have a higher allocative efficiency, and vice versa (Pearson correlation of 0.6). Hence, in line with our findings for the East-West comparison, the considerable relationship between productivity and allocative efficiency implies that, also on the state-level, there is a large potential for narrowing regional disparities hidden in fostering the reallocation of employees towards the most productive plants.

To get an impression of the magnitude of this potential, consider the productivity levels in the 2016-2018 period for the most and least efficient states in terms of resource allocation, namely of Rhineland-Palatinate and Mecklenburg-West Pomerania. As shown in Table 3, labor

Table 3: Allocative efficiency and labor productivity in the German federal states

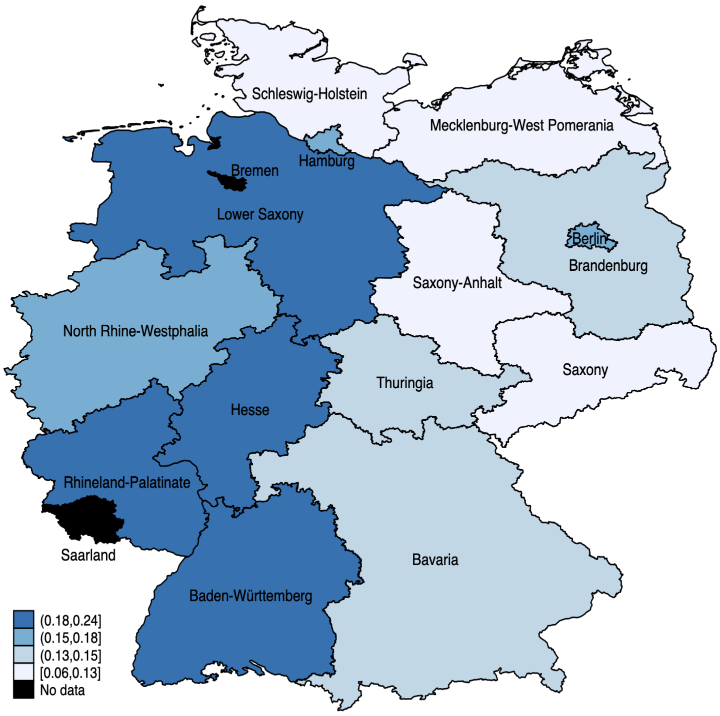
State	Allocative efficiency			Labor productivity		
	2004-2006	2010-2012	2016-2018	2004-2006	2010-2012	2016-2018
Schleswig-Holstein	13.6	10.5	10.7	189.4	186.8	194.3
Hamburg	18.4	20.0	13.6	237.7	266.6	277.2
Lower Saxony	19.9	20.4	16.9	215.5	223.3	213.6
North Rhine-Westphalia	18.4	18.0	16.4	215.2	220.8	211.5
Hesse	19.5	20.7	20.2	191.7	197.1	192.3
Rhineland-Palatinate	22.6	24.7	23.5	201.6	210.4	219.8
Baden-Württemberg	17.5	18.0	19.2	191.5	193.4	201.2
Bavaria	17.4	14.2	12.2	194.9	189.8	185.2
Berlin	21.7	11.9	13.1	205.9	212.3	204.8
Brandenburg	18.3	12.9	12.1	197.4	192.2	196.4
Mecklenburg-West Pomerania	8.3	4.2	4.3	161.3	158.9	166.1
Saxony	14.2	12.7	11.2	155.4	164.1	163.8
Saxony-Anhalt	11.8	11.9	10.9	173.3	188.7	188.0
Thuringia	16.6	14.3	10.0	149.2	163.4	171.5

Notes: The table depicts average allocative efficiency (in percent of aggregate productivity) and labor productivity (in thousand deflated euros in sales per employee) for the three time periods.

productivity between 2016 and 2018 is about 32% higher in the former state (219.8) than in the latter (166.1). Moreover, while almost a quarter of aggregate productivity (23.5%) in the former state can be explained by the efficient allocation of resources between plants, in the latter, the role of resource allocation is minor (4.3%) and contributes only marginally to aggregate productivity. If we now control for this difference in allocative efficiency between the two states by comparing the two states' unweighted averages of plant-level productivity (168.2 and 159.1, respectively), the productivity discrepancy can be reduced by a striking 26 percentage points from 32% to less than 6%. In relative terms, this implies that controlling for the gap in allocative efficiency between the two states reduces the productivity gap to less than a fifth.

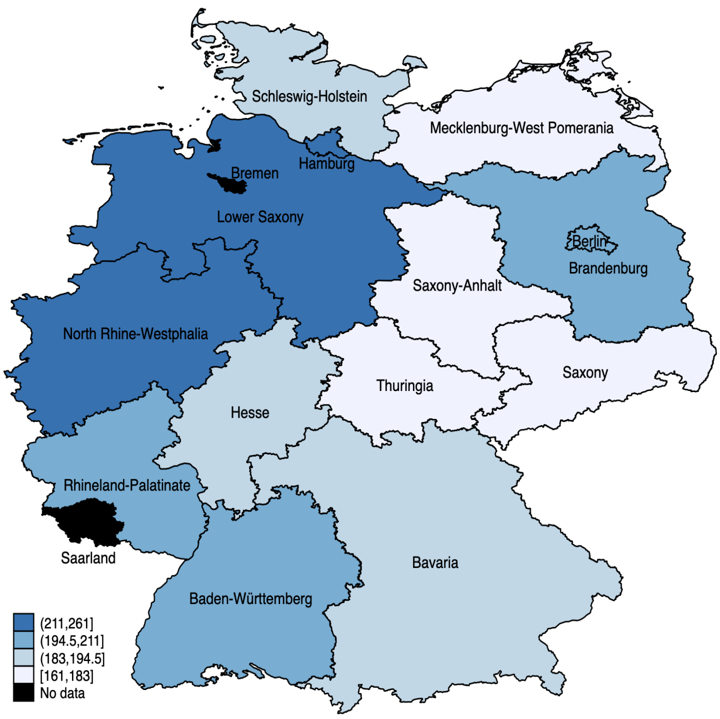
In summary, these results suggest that a large potential for a catching-up process in productivity, especially for East German states, lies in the reallocation of employees towards the more productive plants. Hence, fostering such reallocation processes could substantially contribute to narrowing regional productivity disparities in Germany. This, in turn, raises the question of how best to improve the reallocation of employees towards more productive plants, which we address in Section 6.

Figure 1: Allocative efficiency in the German federal states 2004-2018



Notes: The figure illustrates allocative efficiency in the German federal states. The values are averages of the productivity values for the periods 2004-2006, 2010-2012 and 2016-2018. Former East Germany comprises Mecklenburg-West Pomerania, Brandenburg, Saxony-Anhalt, Saxony, Thuringia and the Eastern part of Berlin.

Figure 2: Labor productivity in the German federal states 2004-2018



Notes: The figure illustrates labor productivity in the German federal states. The values are averages of the productivity values for the periods 2004-2006, 2010-2012 and 2016-2018.

6 Econometric estimation

Our analysis in Section 5 suggests that fostering allocative efficiency could substantially contribute to narrowing regional productivity disparities in Germany. In this section, we intend to provide econometric insights along two lines. First, we estimate the impact of an increase in allocative efficiency on state-level productivity to better grasp the actual potential hidden in the reallocation of employees between plants. Second, we take a first step in the analysis of the drivers of allocative efficiency and reflect on potential policy implications that could leverage the potential of labor reallocation for narrowing the productivity disparities in Germany. Moreover, given that many countries struggle with regional disparities, our goal is to provide insights that may be applicable to other countries as well. For the analyses in this section, we use annual industry-state level values between 2004 and 2018 for all our variables. Note that, due to data constraints, we lack the years between 2007 and 2009.

6.1 Aggregate productivity and allocative efficiency

In this section, we elicit the impact of an increase in allocative efficiency on aggregate productivity. As explained in Section 4, the relationship between aggregate labor productivity and allocative efficiency is more ambiguous as it seems. In fact, it is possible that an increase in allocative efficiency induces a decrease of aggregate productivity. If this were the case in our sample, the suggestion of policy implications that increase allocative efficiency would be counterproductive.

Therefore, as a first step, we empirically show for our sample that an increase in allocative efficiency entails, in fact, an increase in aggregate productivity. To elicit the impact of an increase in allocative efficiency on aggregate productivity, we conduct a simple linear panel regression regressing aggregate labor productivity per state and industry on allocative efficiency, represented by the Olley-Pakes covariance term as a percent share of industry-level labor productivity. To control for unobserved heterogeneity, we include year, state and industry fixed effects.

Table 4: Relationship between industry-level labor productivity and allocative efficiency

	(1) Industry-level labor productivity
OP Covariance (%)	1.059***
	(0.074)
Constant	164.8***
	(1.860)
Observations	1,008
No. of industry-state combinations	84
R-squared	0.289
R2 (adj)	0.215
Year FE	✓
State FE	✓
Industry FE	✓

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

As was to be expected, we detect a highly significant, positive correlation between industry-level labor productivity and allocative efficiency (see Table 4). Given that average productivity across all industries and years in our sample is at around 196.5 thousand euros per employee, we can derive from the coefficient of 1.059 for the OP covariance term that, on average, a one percentage point increase in allocative efficiency is associated with an about 0.54% increase in industry-level labor productivity. This significant and substantial correlation underlines how an efficiency increase in labor allocation could path the way towards a productivity catch-up of the less efficient regions in Germany.

6.2 Allocative efficiency and regional industry characteristics

Having shown the significant correlation between allocative efficiency and aggregate productivity in the German federal states, we now turn to the analysis of the potential causes of the observed regional differences in allocative efficiency.

Before we present our regression model for investigating the extent to which allocative efficiency can be associated with regional industry characteristics, we want to briefly address two important macroeconomic events that may affect the patterns observed in our data. First, it is conceivable that the Great Recession from 2007-2009 affects the allocation of labor among German manufacturing plants in our sample. There is abundant literature on the impact of financial and economic crises on resource (re)allocation. However, the findings are ambiguous. On the one hand, there is the wide-spread view that economic crises enhance the reallocation of resources from the least towards the most productive firms. The underlying idea of this 'cleansing effect' is that an economic downturn makes it more difficult for less productive firms to maintain their market shares, eventually forcing them out of the market (see e.g., Caballero and Hammour, 1994; Foster et al., 2016; Kozeniauskas et al., 2022). On the other hand, several studies show that the distortions caused by economic crises, in particular in credit markets, can negatively affect reallocation dynamics (see e.g., Foster et al., 2016; Osotimehin and Pappadà, 2017). Moreover, economic crises frequently entail government interventions that aim to dampen the impact of the crisis on firms, for instance, through favorable loan agreements or subsidized furlough schemes. As these policies disproportionately benefit less productive firms, such interventions can hinder the reallocation of employees towards their most productive uses (see e.g., Kozeniauskas et al., 2022).

Given these findings, it is likely that the aftermath of the Great Recession affects our results during the 2010-2012 period, and possibly the 2016-2018 period. Compared to the 2004-2006 period, we have identified a general decrease in allocative efficiency in many states, which may be partly caused by the described negative effects of financial and economic crises. The study by Grebel et al. (2022) corroborates this explanation. They find evidence for factor misallocation in German manufacturing after the Great Recession, which they link to, among other aspects, significant labor hoarding in German establishments.

Yet, this explanation is inconsistent with our observation that several West German states experience an increase in allocative efficiency after the Great Recession. Hence, assuming that the Great Recession actually did have a significant impact on reallocation dynamics in Germany, it seems that this impact differs across regions. To explain this versatile impact and, more generally, the heterogeneous development of allocative efficiency in the federal states requires an examination of regional characteristics, as done in our regression analysis.

As a second important aspect on the macroeconomic level, the former East-West division may serve as an explanation for the observed patterns. One feels tempted to attribute the significantly lower allocative efficiency in East Germany to the fact that Germany was, until 1990, divided into a Western market economy and an Eastern centrally-planned economy. Market economies are generally perceived as more efficient in the allocation of resources compared to centrally planned economies. The study by Bartelsman et al. (2013) indicates this relationship, revealing low values for allocative efficiency in Central and Eastern European countries at the beginning of their transition to a market economy. As the transition continues, their study detects a simultaneous increase in allocative efficiency in these countries. Despite its appeal, this explanation is not a satisfactory one for the German case. As reported in the previous section, instead of an increase in allocative efficiency with the ongoing transition from a planned to a market economy, we observe a substantial decrease in former East Germany between 2004 and 2018. Hence, even though it is possible that the former East-West division partly explains the Eastern deficit in allocative efficiency, the subsequent decrease in allocative efficiency shows that further drivers must be involved. Moreover, focusing on East-West differences cannot explain why we observe large differences in allocative efficiency among East German states. Therefore, in our regression model, we investigate the drivers of allocative efficiency at the more fine-grained, regional level.

6.2.1 Regression model

Following our explanations in Section 2 with respect to essential drivers of allocative efficiency, we included three different regional industry characteristics available in our database, computed annually for each state and industry: export intensity (ExpInt: exports per sales in %), the Herfindahl index (HHI: sum of squared sales market shares) and the mean plant size (lnMPS: log of plant size in employees per plant). To control for unobserved heterogeneity, we include year, state and industry fixed effects.

As the first industry characteristic in our regression, we use export intensity as a proxy for trade openness. Melitz (2003) shows that exposure to trade is positively correlated with inter-firm resource reallocation, that is, allocative efficiency, due to two types of selection effects. First, only the most productive firms self-select into and thereby benefit from export markets as the entry into export markets entails costs which only they can afford. Second, trade exposure prohibits the least productive firms to earn positive profits and eventually forces them to exit the market. Hence, in our regression exercise, we expect a positive relationship between export intensity and allocative efficiency.

As our second independent variable, we deploy the Herfindahl index (HHI) as a measure of market concentration and a proxy for (the inverse of) competitive intensity. Despite certain drawbacks, using the Herfindahl index as a proxy for competition is a widely applied practice, particularly when no data is available on plant-level profits that would allow for an arguably more appropriate measure (see e.g., Aghion et al., 2005; Boone, 2008).

Our hypothesis regarding the relationship between market concentration and allocative efficiency can be divided into two lines of argument. On the one hand, there are aspects pointing towards a positive correlation between market concentration and allocative efficiency. To start with, one may argue that higher market concentration leads to more innovation driven by the largest players due to higher expected rents, sometimes referred to as the 'Schumpeterian effect' (Aghion et al., 2005; Schumpeter, 1942). As pointed out by Mohnen and Hall (2013), more innovation tends to translate into higher productivity. Hence, if the largest plants become more productive, this exerts a positive influence on allocative efficiency. A second argument in favor of a positive correlation between market concentration and allocative efficiency arises when assuming the existence of relevant economies of scale within a respective industry. In such an industry, plants with the highest market share also tend to possess the highest productivity levels. If market concentration increases, it is conceivable that these largest plants will benefit from even higher economies of scale relative to their competitors. This would further widen the gap among the largest, most productive and the smallest, least productive plants, which is tantamount to higher allocative efficiency. On the other hand, a high degree of market concentration, that is, weak competitive intensity may also decrease innovation and thereby productivity growth. Arrow (1962) argued that the incentive to innovate is higher in a less concentrated, more competitive industry than under monopolistic conditions. The idea is that a monopolist who already enjoys high profits has only little incentive to replace these profits by innovating, compared to new entrants (Bloom et al., 2019). If we follow this line of argument, an increase in market concentration can be linked to a decrease in allocative efficiency, as it weakens the incentive for the dominating players with high market shares to innovate and increase their productivity. Moreover, lower competition intensity is typically associated with a less stringent market selection process, making it easier for the least productive plants to maintain their market shares and stay in the market (Syverson, 2011; Brown et al., 2018). Therefore, low competitive intensity may weaken the reallocation of workers towards the most productive plants and thereby decrease allocative efficiency.

In sum, there is a certain dichotomy in the relationship between market concentration and allocative efficiency. It is conceivable that the positive or the negative association dominates while it is also possible that we will see an outcome that reconciles the two opposed perspectives, which could, for instance, translate into an inverse U shape relationship. To test for such a relationship, we include a squared term for the HHI in our regression. The ambiguity may not come as a surprise, given that our above reasoning is significantly inspired by the debate on the relationship between competition or market concentration and innovation, where, both theoretically and empirically, this dichotomy remains unresolved (see e.g., Scherer, 1967; Cohen and Levin, 1989; Aghion et al., 2005; Bloom et al., 2019). We further comment on this below when discussing our regression results.

As the third industry characteristic in our regression we included the mean plant size. A higher average plant size can be associated with increased economies of scale. We expect the more productive and larger plants within an industry to benefit in particular from these economies of scale, increasing the gap to the less productive and smaller plants within the industry. Hence, a higher mean plant size may contribute positively to the OP covariance term. Besides facilitating economies of scale, a high average plant size typically implies high entry barriers which shield incumbents from new competition. This, in turn, may correspond to lower competitive intensity for incumbents. As explained above, the relationship between competitive intensity and allocative efficiency is ambiguous. Following the Schumpeterian paradigm, it is conceivable that the higher entry barriers allow for larger monopoly rents, which would be associated with more innovation of the largest firms and higher allocative efficiency. However, it is also possible that the lower competitive pressure reduces innovation incentives and decreases the reallocation of resources toward the most productive firms. To reflect this ambiguity in our regression, we include a squared term for the mean plant size.

By conducting our regression analysis on the state-industry level, we inherently assume that each industry in each state can be considered an isolated unit. Hence, even when dealing with the same industry, we assume the three above-described industry characteristics to be different for this same industry in each of the German states within our analysis. Naturally, the manufacturing plants within our dataset can be assumed to compete not only within but also across state borders. As a consequence, our analysis overestimates intra-state competition effects while downplaying cross-state relationships. To test for the presence of spatial correlation in our regression results, we included a control variable capturing the mean of the covariance term for the neighboring states for each respective state. While this endeavor does indeed reveal a significant positive correlation, our findings regarding the relevance of state-level industry characteristics still hold (see Table 5).

6.2.2 Results

Our regression results are reported in Table 5. As shown, we introduce our variables sequentially in order to show the robustness of the results. We further control for year, state and industry fixed effects. Unless otherwise stated, we refer exclusively to the coefficients in model (6).

With respect to export intensity, we observe a highly significant positive relationship with allocative efficiency. This confirms our expectation that trade openness can be linked to the reallocation of resources towards the most productive firms.

Concerning the relationship between the HHI and allocative efficiency, we find confirmation of the inverse U shape relationship, which is reflected in a positive coefficient of the linear term and a negative coefficient of the squared term. The positive linear term implies that, at low levels of market concentration, the effects supporting a positive correlation between market concentration and allocative efficiency dominate, namely increased economies of scale and the Schumpeterian effect. The negative coefficient of the squared term, in contrast, indicates that this dominant positive correlation only holds until a certain threshold of market concentration is breached. If an industry passes this threshold, a further increase in market concentration is associated with a decrease in allocative efficiency, which we attribute to the very low competitive intensity in such industries. In fact, computing the HHI that maximizes the U-shaped function results in an HHI of around 0.34, which represents the 99^{th} percentile in the distribution of HHI in our data. This implies that the effects supporting a positive correlation between market concentration and

Table 5: Allocative efficiency and industry characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
			OP Covariance (%)			
ExpInt	0.449***	0.344***	0.397***	0.321***	0.326***	0.307***
	(0.040)	(0.039)	(0.043)	(0.043)	(0.043)	(0.043)
HHI		94.69***	102.8***	252.2***	237.2***	231.3***
		(8.698)	(9.136)	(23.304)	(23.413)	(23.130)
HHI^2				-406.7***	-361.4***	-337.4***
				(58.640)	(59.240)	(58.641)
lnMPS			-4.558***	-7.011***	69.72***	69.95***
			(1.623)	(1.622)	(19.146)	(18.891)
$lnMPS^2$					-8.371***	-8.464***
					(2.082)	(2.054)
OPCovNeighbors						0.253***
						(0.050)
Constant	5.942***	4.391***	22.82***	30.72***	-143.8***	-146.8***
	(1.177)	(1.117)	(6.656)	(6.589)	(43.883)	(43.303)
Observations	1,008	1,008	1,008	1,008	1,008	1,008
Industry-state combinations	84	84	84	84	84	84
R2 (adj)	0.101	0.203	0.209	0.248	0.261	0.280
Year FE	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

allocative efficiency seem to outweigh the ones supporting a negative relationship.[6]

With respect to the correlation between the mean plant size and allocative efficiency, our regression results show a positive coefficient for the linear term and a negative coefficient for the squared term. In analogy to the HHI, this indicates an inverse U shape relationship between the mean plant size and allocative efficiency. For industries with a small mean plant size, an increase in the mean plant size corresponds to an improvement in allocative efficiency. As explained above, this could be due to an increase in economies of scale and the Schumpeterian effect on innovation. We observe this positive correlation between plant size and allocative efficiency up to a plant size of around 62 employees. This threshold represents the 13th percentile in the distribution of mean plant size in our database, implying that the large majority of industries in the German manufacturing sector are above this optimal mean plant size. After passing this threshold, a further increase in the mean plant size is associated with a decrease in allocative efficiency. We trace this decrease back to the competition-reducing impact of heightened entry barriers, which appears to outweigh the Schumpeterian effect and increased economies of scale.

[6]The clear dominance of this positive relationship is surprising, given our previous statements regarding the ambiguity of the relationship. A possible reason consists in the measure we deploy as a proxy for competitive intensity. Despite being widely deployed, a high HHI, that is, high market concentration, is not necessarily associated with low competition (see e.g., Aghion et al., 2005). This may weaken the negative relationship between market concentration and allocative efficiency, which essentially rests on the assumption that higher market concentration implies lower competitive intensity, which would weaken the reallocation of workers towards the most productive firms.

6.2.3 Discussion and policy implications

Our regression analysis has shown that regional discrepancies in allocative efficiency are significantly associated with regional differences in export intensity, market concentration and plant size. Note that we only document associations between these variables, as endogeneity prevents us from making any causal claims. To address this issue, we also ran the regression with time-lagged independent variables as instruments (see Appendix C). Nonetheless, due to data constraints, the issue of endogeneity cannot be fully eliminated. Hence, our ensuing reflections on potential policy implications are to be seen against this background.

First, we have detected a positive relationship between export intensity and allocative efficiency which is in line with the literature (see e.g., Melitz, 2003). This finding suggests that policies aimed at the intensification and liberalization of trade have a positive impact on allocative efficiency. Second, our regression has revealed a significant inverse U shape relationship between market concentration and allocative efficiency. Competition policies are typically aimed at preventing high levels of market concentration. With respect to its impact on allocative efficiency, our results indicate that an increase in market concentration up to a certain threshold can be beneficial. However, in very highly concentrated industries, this positive relationship deteriorates. Hence, in these industries, policies aimed at taming market concentration (e.g., via antitrust authorities) or fostering competition would be associated with higher allocative efficiency. Third, we have identified a significant inverse U shape relationship between the mean plant size within an industry and allocative efficiency. Therefore, in industries with a small average plant size, policies aimed at facilitating plant growth may induce an increase in allocative efficiency as it enables the benefiting from economies of scale and higher expected returns for innovators. However, this relationship is reversed for higher mean plant sizes which can be attributed to higher entry barriers and the subsequent decrease in competition intensity. For these industries, policies that increase competition and facilitate market entries of new plants can be expected to positively affect allocative efficiency.

7 Conclusion

In this study, we have shown that regional variation in the efficiency of labor allocation among manufacturing plants plays a major role in explaining regional productivity disparities in Germany. The market selection process that steers employees towards the most productive plants appears to work less efficiently in East than in West Germany. Yet, our results also reveal that the mere focus on East-West comparisons hides partially large differences between German states. We show that these regional productivity differences could be substantially narrowed by fostering labor reallocation processes. With respect to the causes of the observed variation in allocative efficiency, our regression results indicate that the variation is significantly associated with regional differences in export intensity, market concentration and plant size. For export intensity, we find that policies aimed at the intensification and liberalization of trade can increase allocative efficiency. Regarding the impact of market concentration and plant size on allocative efficiency, we find an inverse U shape relationship. Therefore, policy implications with respect to these industry characteristics depend on the circumstances of the individual region and industry.

The regression results presented in this study can be a first step towards explaining the observed regional differences in allocative efficiency. Future research in this field should attempt to extend the analysis to shed more light on the causes of the observed regional patterns in allocative efficiency. For instance, it would be insightful to include a measure for competitive intensity that is not based on market concentration (as is the Herfindahl index), because a highly concentrated industry does not necessarily entail low competition. Therefore, including measures such as the price cost margin (see e.g., Aghion et al., 2005) could help distinguish between the impact of market concentration and competitive intensity. In addition, further research might explore the role of labor mobility for allocative efficiency in Germany. As pointed out by Syverson (2011), more flexible input markets can be assumed to enhance the reallocation of resources towards their most productive applications. One possibility to analyze this relationship in Germany consists in using the Linked Employer-Employee Data from the German IAB (LIAB). Even though this database relies on a smaller sample of plants than the sample used in our study, it allows for an accurate measure of job destruction and creation rates. Correlating these measures with allocative efficiency would show whether fostering labor mobility could help reduce regional productivity differences. Apart form investigating industry characteristics, it could be interesting to extend our analysis by investigating the effects of metropolitan areas on regional allocative efficiency. Larger cities typically exhibit higher levels of productivity, driven by, among others, agglomeration effects (such as enhanced labor market pooling) and increased market selection mechanisms (see e.g., Combes et al., 2012). An analysis of these effects influence allocative efficiency in Germany would require a more fine-grained, regional analysis (e.g., NUTS2), which will reduce the available number of plants per region. This also implies that fewer industries and fewer regions could be covered in such an analysis as they do not reach the minimum number of plants necessary for reliably computing allocative efficiency. Nonetheless, even for a limited sample, such an analysis could reveal interesting insights.

To conclude, this study demonstrates that the improvement of allocative efficiency is a promising avenue for narrowing regional disparities in Germany. However, even though we focus on Germany, we expect other countries to show similar regional variations in allocative efficiency. Evidently, given its history as a divided country with two different economic systems, regional analyses in Germany have certain idiosyncrasies. Nonetheless, the identified drivers of allocative efficiency, such as differences in export intensity, market concentration, or plant size, can be expected to also apply for other countries. Therefore, studying regional variations in allocative efficiency in other countries may be a fruitful area for future work.

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A Industry classification and summary statistics

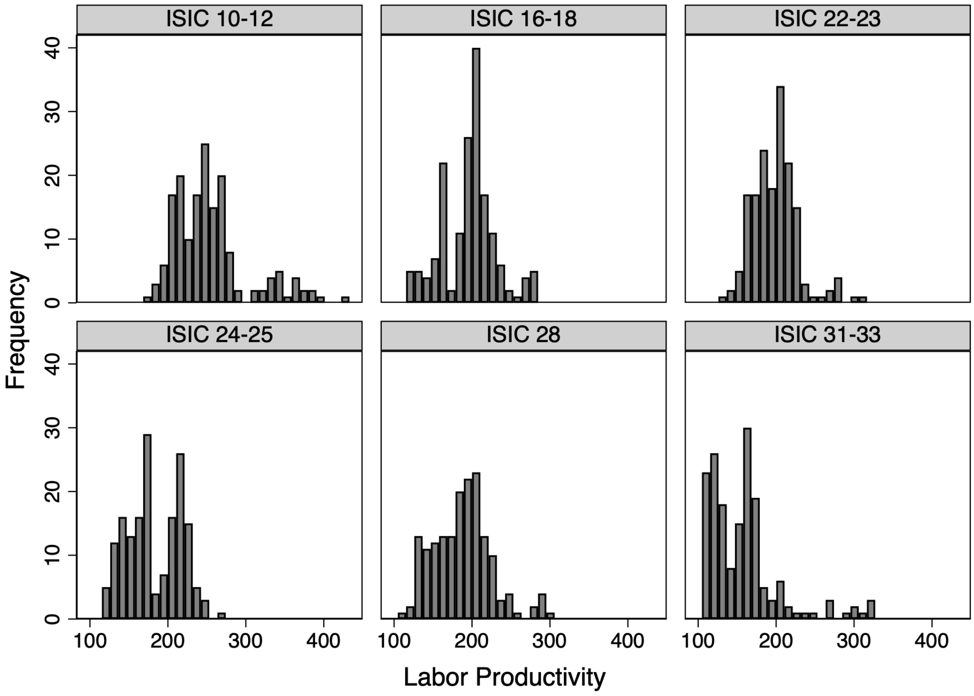
Table A1: Industry classification and summary statistics

ISIC	Description	Plants	Empl.	Prod.
2004-2006				
10-12	Food products, beverages and tobacco products	5,155.3	450.8	253.0
16-18	Wood and paper products; printing and reproduction of recorded media	3,732.3	307.4	188.0
22-23	Rubber and plastics products, and other non-metallic mineral products	5,539.0	488.1	185.2
24-25	Basic metals and fabricated metal products, ex. machinery and equipment	6,941.7	703.6	201.7
28	Machinery and equipment n.e.c.	5,944.7	737.7	194.1
31-33	Other; repair and installation of machinery and equipment	3,367.7	337.0	173.5
2010-2012				
10-12	Food products, beverages and tobacco products	5,057.0	469.2	253.8
16-18	Wood and paper products; printing and reproduction of recorded media	3,262.3	284.7	205.3
22-23	Rubber and plastics products, and other non-metallic mineral products	5,383.0	496.4	199.2
24-25	Basic metals and fabricated metal products, ex. machinery and equipment	7,466.3	751.8	194.4
28	Machinery and equipment n.e.c.	5,144.7	801.6	199.9
31-33	Other; repair and installation of machinery and equipment	4,156.7	375.1	169.0
2016-2018				
10-12	Food products, beverages and tobacco products	5,220.3	521.3	245.1
16-18	Wood and paper products; printing and reproduction of recorded media	3,045.3	284.4	208.9
22-23	Rubber and plastics products, and other non-metallic mineral products	5,606.3	540.7	197.5
24-25	Basic metals and fabricated metal products, ex. machinery and equipment	8,007.7	821.7	193.2
28	Machinery and equipment n.e.c.	5,422.0	887.7	205.0
31-33	Other; repair and installation of machinery and equipment	4,431.3	395.6	161.6

Notes: The table shows the Germany-wide averages of annual industry-level values for plant count, employment and labor productivity during the three periods considered in our study. All values are based on the cleaned sample as documented in Section 3. Employment is reported in thousands and labor productivity is measured as thousand deflated euros in sales per employee.

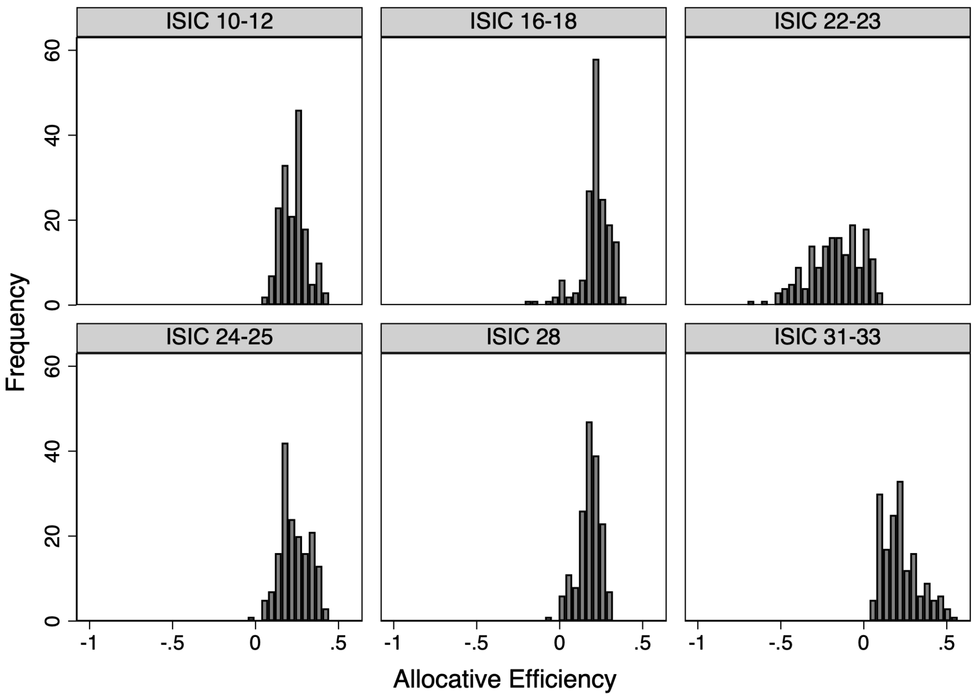
B Heterogeneity in labor productivity and allocative efficiency across states and industries

Figure B1: Labor productivity in different manufacturing industries and states



Notes: The figure depicts the frequency of observations for annual state-level labor productivity of the 14 states within the six industry classifications between 2004 and 2018.

Figure B2: Allocative efficiency in different manufacturing industries and states



Notes: The figure depicts the frequency of observations for annual state-level allocative efficiency of the 14 states within the six industry classifications between 2004 and 2018.

C Regression with time-lagged variables

The table replicates the regression from Section 6 with time-lagged independent variables. As shown, all the conclusions we derived in the main text can be maintained with time-lagged values. The only relevant difference is the fact that the relationship between the time-lagged mean plant size (L.lnMPS) and allocative efficiency becomes significant only when simultaneously including the time-lagged squared term (L.lnMPS^2) in the model (models 5 and 6). As soon as the relationship turns significant, the signs of the coefficients are identical to the ones in our regression in the main text.

Table C1: Allocative efficiency and time-lagged industry characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
	OP Covariance (%)					
L.ExpInt	0.365***	0.299***	0.286***	0.204***	0.207***	0.193***
	(0.047)	(0.048)	(0.052)	(0.052)	(0.052)	(0.052)
L.HHI		61.84***	59.47***	219.4***	208.4***	206.2***
		(10.835)	(11.559)	(27.780)	(27.849)	(27.755)
L.HHI^2				-447.8***	-410.0***	-397.9***
				(71.123)	(71.766)	(71.644)
L.lnMPS			1.217	-1.466	69.92***	70.31***
			(2.067)	(2.060)	(23.155)	(23.067)
L.lnMPS^2					-7.828***	-7.926***
					(2.529)	(2.520)
L.OPCovNeighbors						0.162***
						(0.063)
Constant	8.475***	7.394***	2.432	11.19	-150.5***	-152.7***
	(1.345)	(1.331)	(8.531)	(8.433)	(52.900)	(52.705)
Observations	840	840	840	840	840	840
Industry-state combinations	84	84	84	84	84	84
R2 (adj)	0.0304	0.0697	0.0689	0.115	0.125	0.132
Year FE	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.