Monopsony Makes Firms not only Small but also Unproductive: Why East Germany has not Converged

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Abstract

When employers face a trade-off between being large and paying low wages—and in this sense have monopsony power—some productive employers decide against building large business networks, forgo sales, and remain small. These decisions have adverse consequences for aggregate labor productivity. Using high-quality administrative data from Germany, we document that East German plants (compared to West German ones) face steeper size-wage curves, invest less in their business networks, remain smaller, and are less productive. A model with labor market monopsony, product market power, and business network investments matching these features of the data predicts a ten percent lower aggregate labor productivity in East Germany.

Keywords: aggregate productivity, plant heterogeneity, collective bargaining, monopsony power, size-wage curve, business networks, customer capital, size distortions

JEL: E20, E23, E24, J20, J42, J50

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1 Introduction

Union membership around the world has declined. This decline did not happen uniformly but was most pervasive at small plants. Importantly, as union-/collectively-bargained wages are higher, this non-uniform union retrenchment effectively leads to firms facing a size-wage trade-off and, in this sense, to some form of monopsony power. East Germany has seen a particularly skewed union-retrenchment compared to West Germany. As a result of this non-uniform union decline, the size-wage curve is steeper in East than in West Germany. In the communist German Democratic Republic, trade unions did not represent worker interests. As a consequence, after reunification, union membership fell dramatically (see Schnabel, 2005); most pronounced at small plants. At the same time, East and West Germany share the same legal and, by and large, cultural institutions. Therefore, the East and West German comparison provides a good laboratory to study how firms' employment and business strategy decisions respond to monopsony power in the labor market and how this influences aggregate productivity.

We use this variation in size-wage curves to show that stronger monopsony power creates incentives for firms in East Germany to choose small-scale business models when they start up. Consequently, even the most productive firms hire relatively few workers and create smaller business networks, i.e., they acquire fewer customers. Monopsony power, thus, distorts firms' investment decisions in their business models at entry. This distortion creates a compressed size distribution of firms in East Germany and sizable aggregate productivity effects. Thirty years after the German reunification, labor productivity and wages remain about 25 percent lower in East Germany, and the disincentives from a steeper size-wage curve explain at least ten percentage points of this gap.

We arrive at this conclusion by employing high-quality administrative wage data and a new calibrated heterogeneous-firm model. We document that, in the data, aggregate and industry differences in labor productivity and wages are systematically related to the absence of large plants in East Germany.[1] The share of employment at large plants with more than 249 employees is almost twice as large in the West. This difference is manifest already at plant entry and persists.

[1] Most firms are essentially single-plant, and our data is of high quality at the plant level.

In industry-level data, there is a positive correlation between missing large plants and the East-West productivity/wage gap. For example, vehicle manufacturing has both a particularly large East-West gap in labor productivity (36%) and in the concentration of employment at large plants (21 percentage points), while construction has a smaller labor productivity gap (14%) and virtually the same employment concentration at large plants in East and West Germany.

For these findings, wage data provide an explanation: The plant size elasticity of wages is one fifth larger in East Germany relative to West Germany and this, in turn, is explained by larger differences in collective bargaining between large and small plants in East Germany. Exploiting again differences across industries, we show that those industries with steeper size-wage curves in the East are also those industries with particularly low average wages and particularly many missing large plants, which is again already manifest at entry.

Finally, we show that East German firms invest less in business networks. Across industries, this is, yet again, systematically related to size-wage curve differences: Industries that face particularly steep size-wage curves in East Germany have particularly small customer networks and investments in them.

To quantify the effects of a steeper size-wage trade-off on the plant/firm size distribution and aggregate labor productivity, we employ a Melitz (2003)-type heterogeneous-firm model with variety-loving final-good bundlers. To this model, we add customer acquisition (in the spirit of Sedláček and Sterk, 2017; Arkolakis, 2010) and labor market power (as in Berger, Herkenhoff, and Mongey, 2022). Given that the effects of the size-wage curves are manifest already at entry, we model long-run optimal firm decisions in a static framework, which also allows us to characterize the solution in closed form. In our model, firms first decide about market entry; second, conditional on entry, they learn their productivity and decide on investments in their business network. Third, firms hire labor and produce, facing both a size-wage and an output-price trade-off. We show that monopsony power affects all of these decisions. As it increases profits, it boosts firm entry, but it also incentivizes firms to choose a smaller-scale business model.

We also show that the effects of labor market monoposony power on business model choice dominate those on entry, leading to less efficient production networks, as the average variety-loving final-good bundler bundles from fewer firms.

In addition, monopsony power works through a labor allocation channel: It compresses the employment distribution and, thus, reallocates labor from more to less productive firms.

We calibrate the model, implicitly assuming single-plant firms, to the average plant size and the share of large plants in West Germany. Imposing the steeper size-wage curve from East Germany as a menu for the firms in our model to choose from reduces aggregate labor productivity by ten percentage points. Smaller business networks explain half of this number, labor reallocation to less productive firms explains the other half. In addition, untargeted, the model, parsimoniously, replicates the plant size distribution in East Germany closely. For the manufacturing sector, where East-West differences in plant size, the size-wage trade-off, and aggregate productivity are particularly pronounced, the calibrated model explains 18 percentage points lower productivity in East Germany.

The paper proceeds as follows: First, we review the literature. Then, Section 2 discusses our data sets. Section 3 provides the empirical analysis. Section 4 introduces our model, and Section 5 discusses its quantitative implications. Section 6 concludes. We relegate additional material to a number of appendices, in particular a discussion of alternative explanations for East-West differences in aggregate labor productivity (Appendix A) and plant size (Appendix B).

Literature First, our paper is related to the literature that explains aggregate productivity losses as a result of too little employment at the most productive plants. For example, Hsieh and Klenow (2014) and Braguinsky, Branstetter, and Regateiro (2011) take the relatively slow growth of plants/firms as evidence of high (implicit) taxes on growing large and quantify the resulting productivity loss. More recently, the literature, like our paper with collective bargaining, starts from existing institutions like firing protections and links them to aggregate productivity losses caused by their effects on the plant/firm size distribution. Examples include Garicano, Lelarge, and Van Reenen (2016) and Cingano, Leonardi, Messina, and Pica (2016). Our paper highlights a new force behind productivity losses from a compressed plant/firm size distribution: steeper size-wage trade-offs.

As we have argued, steeper size-wage trade-offs result in a form of monopsony power that firms have when choosing the size of their business network. Recently, Berger et al. (2022) have also highlighted monopsony power as a force that reallocates labor from more to less productive firms. Their focus is on the employment decisions given a firm's business model, while ours is on a distortion affecting the long-term choice of the business model itself.[2] Consequently, they use fluctuations in corporate taxes as shifters of labor demand to identify monopsony power. In our case, higher wages at larger firms do not arise directly as a means to attract more workers but indirectly from an increased incidence of collective bargaining. We view both perspectives on monopsony power as complementary.

Second, our paper relates to the large literature on productivity (non-)convergence between countries in general (see Johnson and Papageorgiou, 2020, for a recent survey), as well as former socialist countries in particular (see Svejnar, 2002, for a survey). We study non-convergence within a country and, thus, non-convergence within the same legal framework.[3] Our focus, therefore, differs from those earlier studies that examine the challenges faced by other former socialist countries which had to build their own strong legal institutions. Studying non-convergence within a country has the additional advantage that we can use high-quality micro data with common measures of factor inputs across the regions.

Non-convergence within Germany has drawn attention in the literature, particularly because convergence had been expected after reunification (see Boltho, Carlin, and Scaramozzino, 1997), given the same (high-quality) institutions in East and West Germany. On the other hand, Becker, Mergele, and Woessmann (2020) and Sleifer (2006) show that East Germany has been nine percent poorer before World War II, and, therefore, full convergence should perhaps not be expected. Today, however, the discrepancy is, with 25 percent, much larger. We explain 40% of today's productivity difference between the two regions or two-thirds of its post World War II increase. Snower and Merkl (2006) study unemployment differences between East and West Germany and relate them to government transfers. Regarding convergence in labor productivity, Burda (2006) emphasizes the

[2]In addition to this more conceptual difference relative to Berger et al. (2022), we focus on monopsonistic, as opposed to oligopsonistic, competition. What is more, we restrict the analysis to allocative effects, abstracting from normative efficiency questions.

[3]Non-convergence can also be found in other countries (Italy's "Mezzogiorno", the US' "Rustbelt", etc.). What makes the German case of regional non-convergence particularly interesting is that there is a well-defined starting date from which onward we should expect convergence (October 3, 1990), a point made by Uhlig (2006).

role of capital accumulation frictions for the slow convergence between the two regions. While capital accumulation has played an important role for convergence right after the reunification, it cannot explain the persistent differences between East and West Germany (see Appendix A). Uhlig (2006) shows that initial conditions, i.e., at reunification, may be self-perpetuating when agglomeration effects in production networks are important. In our model, differences in business networks also play a role. They arise, however, endogenously from differently steep size-wage curves that reduce the average productivity of a job. In fact, using cross-border worker mobility, Fuchs-Schündeln and Izem (2012) find that job, in contrast to worker, characteristics explain lower wages in East Germany. Using matched employer-employee data, Heise and Porzio (2021) document a low mobility of German workers across the two parts of the country. What is more, they also find that worker productivity differences between East and West Germany explain little of the overall productivity difference. While their paper takes these plant productivity differences as given and explains why *worker mobility* does not remove East-West German wage differences, our paper explains why plant/firm labor productivity is lower in East Germany, and *firm entry* does not remove these wage differences, either. We, thus, view both papers as complementary.

In terms of model ingredients, our paper marries two literatures. There is a large literature concerned with the labor market effects of monopsony power (Jäger, Roth, Roussille, and Schoefer, 2024; Lamadon, Mogstad, and Setzler, 2022; Berger, Herkenhoff, and Mongey, 2022; Card, Cardoso, Heining, and Kline, 2018; Manning, 2011, 2003; Burdett and Mortensen, 1998). We, by contrast, highlight that monopsony power also distorts long-run investment decisions, e.g., in establishing business networks, through which firms acquire customers. Customer acquisition, in addition to differences in technical productivities, is another force the literature has highlighted to explain the size distribution of plants/firms (see Einav, Klenow, Levin, and Murciano-Goroff, 2021; Sedláček and Sterk, 2017; Gourio and Rudanko, 2014; Drozd and Nosal, 2012; Arkolakis, 2010). We show that, combined with a love-of-variety-in-production argument (see, e.g., Bilbiie, Ghironi, and Melitz, 2012), less customer acquisition leads to lower aggregate labor productivity in a framework with monopsony power in the labor market.

Lastly, our paper relates to the large literature on minimum wages (see Dube and Lindner, 2024, for a recent survey). This literature usually points out that minimum wages reduce employers' monopsony power and can increase aggregate employment (see Azar, Huet-Vaughn, Marinescu, Taska, and Von Wachter, 2024, for a recent example). We abstract from aggregate employment effects and, instead, highlight that reducing monopsony power increases aggregate productivity by reallocating employment to more productive firms and by increasing business networks which increase productivity for all firms. These predictions are consistent with Dustmann, Lindner, Schönberg, Umkehrer, and vom Berge (2022) who show that the introduction of a national minimum wage in Germany in 2015, indeed, led to reallocation of workers to more productive plants. They are also consistent with Ku (2022) and Coviello, Deserranno, and Persico (2022) who both find that minimum wages do increase firm-level productivity.

2 Data

For our analysis, we use administrative aggregate, industry-level, and micro data at the regional level. We focus on the private, non-primary sector (industries 10 to 82 in the German WZ2008 industry classification system). Specifically, we use German national income and product accounts data, *Volkswirtschaftliche Gesamtrechnung (VGR)*, to compute labor productivity at the regional level.[4] The micro data sets are, respectively, the German Structure of Earnings Survey (*SES*), *Verdienststrukturerhebung*, the Administrative Wage and Labor Market Flow Panel (*AWFP*), and the ZEW Mannheim Innovation Panel (*MIP*).

Ideally, all our micro data would be at the firm level because the model is a firm model and this makes sense in the German institutional setting, where collective bargaining happens at the level of the employer in the legal sense, which is the firm, not the plant. However, available plant-level data are of vastly superior scope and quality, and most firms are essentially single-plant firms.

[4] The published regional national account data is only available at the supra-industry level. We thank Dr. Thalheimer from the statistical office of Baden-Württemberg for making data at the industry level available to us.

2.1 Structure of Earnings Survey (SES)

The *SES* is a cross-sectional matched employer-employee data set provided by the Federal Statistical Office of Germany (*Statistisches Bundesamt*). The employer in the data is coded as the plant the employee works at. The *SES* is carried out every four years beginning in 2006. The statistical office randomly samples plants and, by law, these plants are required to provide detailed information on their employees and their employees' monthly working hours, earnings, and contract types. Hence, selection due to nonresponse does not arise. It contains the number of employees at a plant, its industry classification, and its location, dividing Germany into five regions.[5] The sample is representative for the universe of all German plants with at least ten employees.[6] Self-employed workers are not covered.

For our baseline analysis, we employ the 2006, 2010, and 2014 samples, which are prior to the introduction of a national minimum wage in Germany. In a supplementary analysis, we exploit this introduction, using the 2018 sample. We drop all civil servants from our sample as well as all plants where at least 50% of employees are civil servants. Moreover, we restrict the sample to full-time employees for our baseline analysis and provide a robustness check including part-time workers. The final sample contains 2,364,862 worker-plant observations. The 2006 sample uses a different industry classification than the later two samples. As a result, we have to merge some industries to have a consistent industry classification. Table C1 in the Appendix C provides a crosswalk for this merger and shows how it relates to the industries from the national accounts.

The *SES* provides the best available data source for our analysis. First, data on regular earnings, overtime pay, bonuses, and hours paid, both regular and overtime, are extracted from the payroll accounting and personnel master data of plants and transmitted via software interface to the statistical office. Transmission error is, hence, negligible. That is, unlike German social security data, the *SES* reports the

[5]North: Schleswig Holstein, Hamburg, Bremen, Berlin, and Lower Saxony; West: Northrhine-Westphalia; South-West: Hesse, Rhineland Palatinate, and Saarland; South: Baden-Württemberg and Bavaria; East: Thuringia, Saxony, Saxony-Anhalt, Mecklenburg Western Pomerania, and Brandenburg. West Germany summarizes the North, West, South-West, and South. Using a different data set, we provide robustness checks regarding the assignment of Berlin in Appendix B.

[6]This restriction is meant to reduce the administrative burden on small enterprises.

actual (e.g., not top-coded) pay and actual hours worked of employees. Second, it also provides detailed information on workers' sex, age, education, occupation, tenure, and job levels. Third, the survey has information on about 3.2 million employees from roughly 28,700 plants in 2006, 1.9 million employees from 32,200 plants in 2010, and 0.9 million employees from 35,800 plants in 2014.[7]

Over all samples, 87% of all full-time employees work at West German plants. In West (East) Germany, 39% (21%) of full-time employees work at large plants (>249 employees), indicating the missing large plants problem; 45% (31%) of all full-time employees are paid according to a collective bargaining agreement. At large (small) plants 64% (31%) of all full-time employees are paid according to a collective bargaining agreement.[8]

Turning to real wages (all in 2016 Euro, all for full-time employees), over all samples, average hourly real wages are 20 Euro overall, and split by West/East: 21 vs. 14 Euro. They are 22 Euro for collectively bargained wage contracts, and 18 Euro for the non-collectively bargained ones. Workers at small plants receive on average an 17 Euro hourly real wage, and workers at large plants 24 Euro.

In 2006 only, the *SES* data contains also the number of workers at the firm that owns the plant. Comparing for this survey year the plant and firm employment information, we find that 83% of all workers work at the "major plant" of a firm (82% West, 84% East), where we consider a plant "major" if more than 85% of the firm's workforce works at that plant.[9] In other words, most employees work in essentially single-plant firms. Assigning the plant location to the corresponding firm highlights that not only large plants are missing in East relative to West Germany but also large firms: In West Germany, 46% of all full-time employees work at plants belonging to large firms, in East Germany this number is 27%.

[7] The number of sampled employees decreased over time because the sampling probability of plants became smaller to reduce bureaucratic costs. In our analysis, we equalize observation weights across surveys so that all surveys receive equal weight.

[8] In Germany, for a plant to be covered by collective bargaining, the employer needs to agree to join an employer association. Workers can, however, pressure employers to do so by striking (see Jäger, Noy, and Schoefer, 2022). It is natural that unions concentrate such costly efforts on large employers.

[9] We define this cut-off point to account for situations in which a firm has only one physical location, but for organizational/legal purposes has an additional unit organized as a separate plant: for example, a canteen or a traveling sales force.

2.2 Administrative Wage and Labor Market Flow Panel (AWFP) and IAB Establishment Panel (IAB EP)

For some analyses, mainly for longer time series and because of additional information about plants, we supplement the *SES* with the *AWFP* which is a quarterly plant-level data set based on German social security data and which contains daily earnings, not wages, up to the social security cap, i.e., there is top-coding in the earnings part of the data. The *AWFP*'s earnings data are thus inferior to the *SES*'s wage data. The *AWFP* data we use covers the universe of German plants for both West and East Germany from 1996 until 2018 (see Bachmann, Bayer, Merkl, Seth, Stüber, and Wellschmied, 2021; Stüber and Seth, 2018). The *AWFP*'s data source is the Employment History (*Beschäftigten-Historik*, *BeH*) of the German Institute for Employment Research (IAB). The *BeH* is an individual-level data set covering all workers in Germany subject to social security.[10] The information in the *BeH* originates from the notification procedure for social security. Essentially, this procedure requires employers to keep the social security agencies informed about their employees by reporting any start and end date of employment and by annually confirming continuing employment relationships. The *AWFP* aggregates this individual worker data to the plant level.[11]

The *IAB EP* provides additional information for a subset of up to 15,500 plants in the *AWFP*, surveyed annually by the IAB (see Ellguth, Kohaut, and Möller, 2014). For our purposes, we use the information on collective bargaining agreements at the plant level contained in the *IAB EP*.

[10] Marginal part-time workers (*geringfügig Beschäftigte*) have been covered since 1999. The main types of employees not covered by the *BeH* are civil servants (*Beamte*), military personnel, and the self-employed. East German employees were integrated with the West German social security administration only after 1992.

[11] To ensure consistency over time, most variables in the *AWFP*—and all variables used in this paper—are calculated on a 'regular worker' basis. In the *AWFP*, a person is defined as a 'regular worker' when she is employed full-time and belongs to one of the following person groups: 'employees subject to social security without special features', 'seamen' or 'maritime pilots.' Therefore, (marginal) part-time employees, employees in partial retirement, interns, etc., are not counted as regular workers.

2.3 ZEW Mannheim Innovation Panel (MIP)

The ZEW Mannheim Innovation Panel, *MIP*, is a firm-level panel data set that surveys German firms about their innovation, marketing, and sales activities. In particular, it asks every two years a detailed set of questions regarding marketing expenses, business strategies, competitive environments, product characteristics, and, in particular, their customer and supplier networks. We use the 2007–2015 survey waves that report data for the years 2006–2014 in line with our main *SES* sample. The industry coverage is slightly different from the *SES*, but broadly comparable, see Appendix C. We use the confidential data that can be accessed only on site.[12]

3 Empirical Analysis

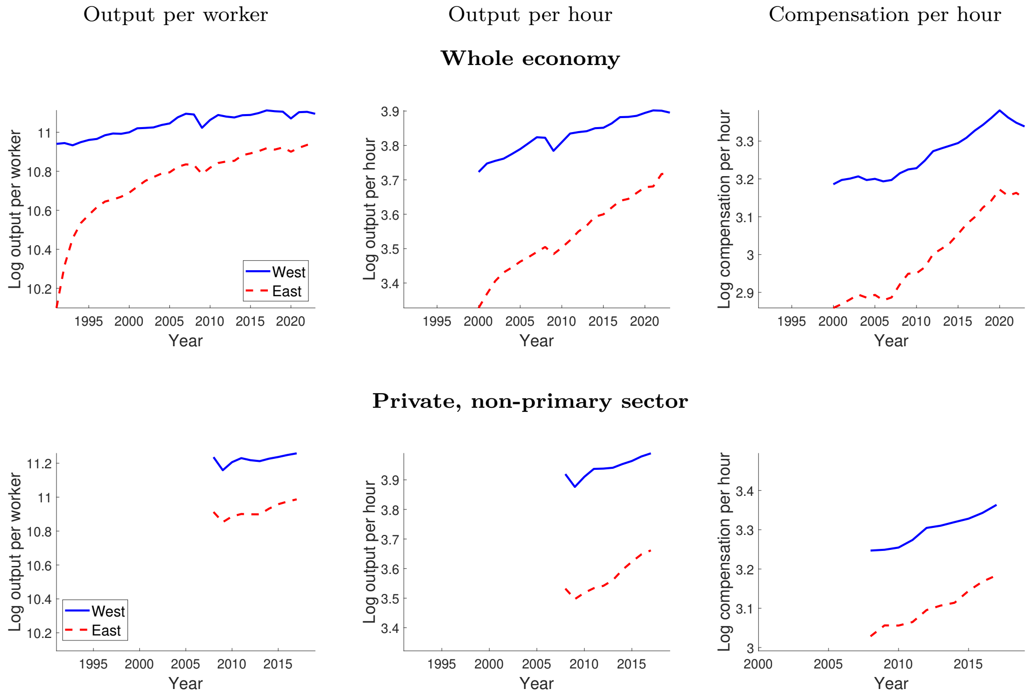
In this section, we document that, at the aggregate level, East Germany has lower labor productivity and labor compensation, whether one includes the public and primary sectors or not. The *SES* data allows us to establish that the lower aggregate and industry-level labor productivity in East Germany is related to missing large plants in the East, which itself is related to a steeper size-wage relationship there, which, in turn, is related to East-West differences in collective bargaining coverage by plant-size. Finally, we establish that East-West differences in size-wage relationships are related to differences in business model choices (at entry).

3.1 Aggregate Productivity

In 1990, when centrally planned East Germany reunited with West Germany and became a market economy, a broad range of factors played an important role in depressing labor productivity: Capital was in short supply, machines were outdated, political pressure had plants overemploy labor in the East, and business customer networks evaporated. Consequently, labor productivity did not even reach 50% of the West German level in 1991 (see the first panel in Figure 1). During the first couple of years after reunification, labor productivity and wages grew rapidly in

[12] We are extremely grateful to the team at the ZEW, in particular Christian Rammer and Sandra Gottschalk, who provided and helped us with the data access.

Figure 1: Output and wages



Notes: The figure displays yearly log real output per worker, yearly log real output per hour, and yearly log real labor compensation per hour in East and West Germany. Output is measured as gross value added, which is the GDP concept available at the regional level, because product-specific subsidies and taxes (the difference between the two) are only available at the national level. The top panel displays it for the whole economy, the bottom panel for the private, non-primary sector. Calculations are based on national accounts (VGR) from 1992 to 2017. The data is available by region and sector only since 2008, which is why the lower panel starts only in that year. Similarly, data on hours worked by region starts in 2000. Weinand and von Auer (2020) provide county-level consumer price indices for Germany in 2016 that we aggregate to the regional level using population weights. With 2016 as the base year, we then calculate a time series of regional prices using the regional GDP-deflator-based inflation rates from national accounts.

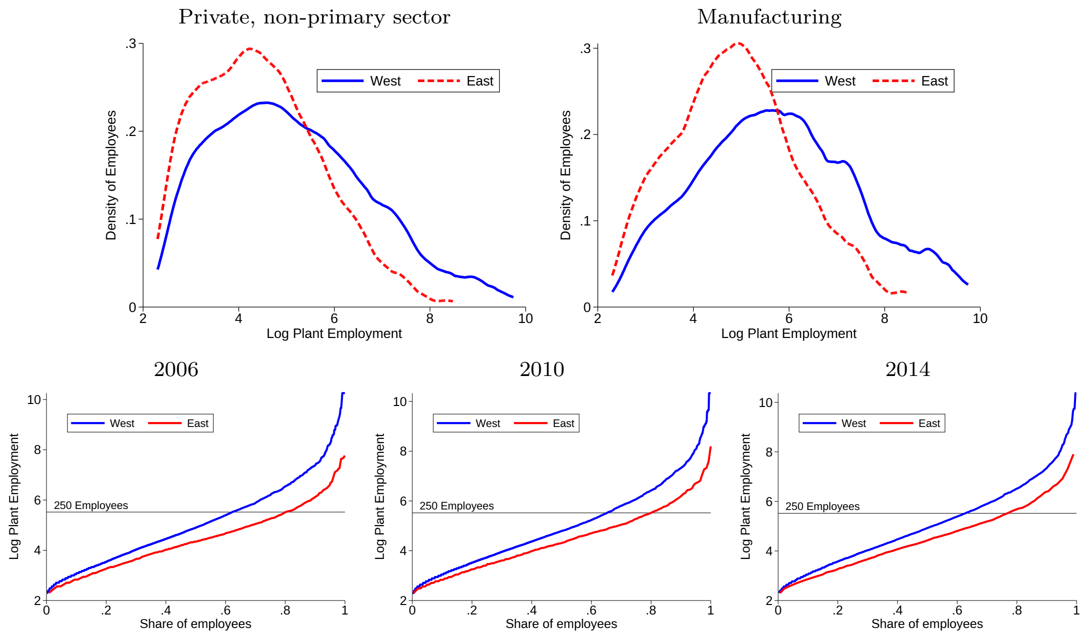
East Germany. However, this process of fast growth ended around 1995. Since then, convergence in labor productivity and wages has almost come to a halt and the difference remains currently at 18%.[13] What is more, as the bottom panel of Figure 1 shows, the East-West productivity difference remains with 25% even larger in the private (non-primary) sector. Finally, the rightmost panels show a similar magnitude for East-West differences in real wages. That wage differences

[13] We use output per worker as our baseline measure of labor productivity. As the figure shows, differences in output per hour are even somewhat larger than those in output per worker.

mirror productivity differences makes the following explanation for productivity differences based on mere accounting unlikely: Headquarters of most large firms are located in West Germany, and, hence, the income from unlocalized intangible capital is accounted for there. Given that we measure productivity as value added productivity, this type of accounting would increase measured West German productivity. Yet, it would leave wages unaffected across the two regions. Therefore, in such a world without other underlying localized productivity differences, wages across the two regions would be the same.

3.2 Missing Large Plants in East Germany

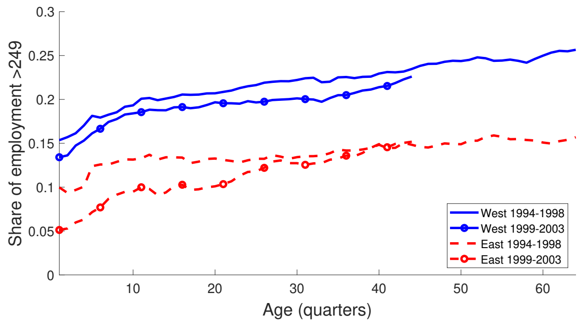
Figure 2: Plant-size distributions in East and West Germany



Notes: The figure displays employment-weighted plant size distributions for East and West Germany. The top panels display, respectively, an estimated density function (by a Gaussian kernel smoother) in the private, non-primary sector and in the manufacturing sector. We pool the 2006, 2010, and 2014 samples. The bottom panels display, for different survey years, what fraction of employees is employed at plants up to a certain size as measured by plant log-employment. Data source: *SES* 2006/10/14.

East Germany has fewer large plants than West Germany in the private, non-primary sector, as can be seen from Figure 2. The top panels show this in terms of

Figure 3: Employment share 250+ by cohort



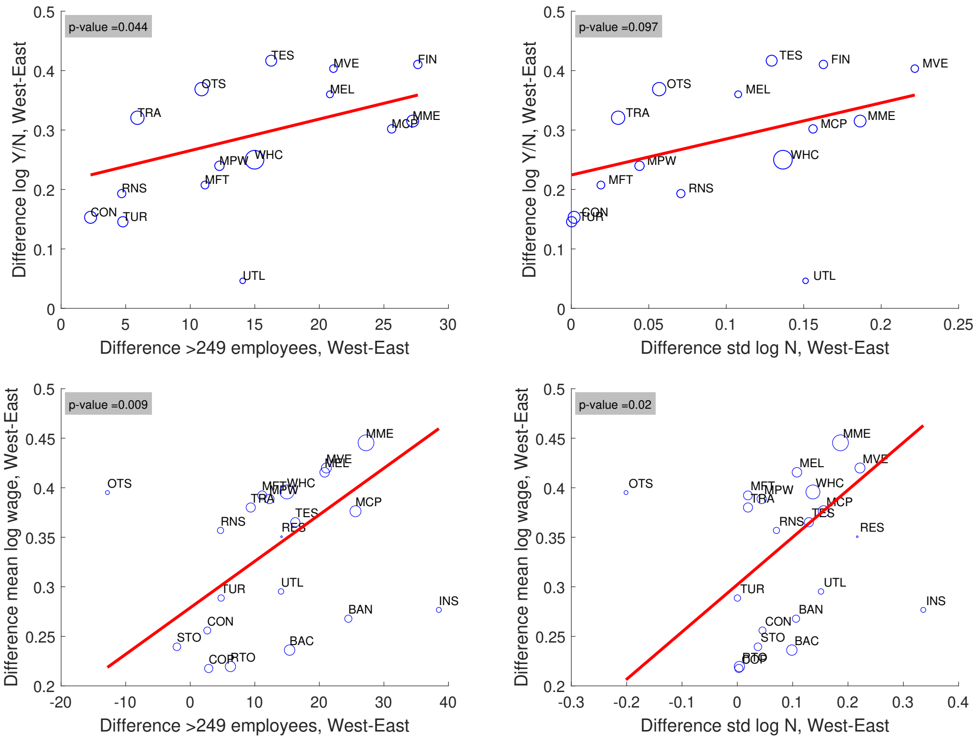
Notes: The figure displays, for the private non-primary sector, for different plant-entry cohorts the share of employment at plants with more than 249 employees over their life-cycles. Data source: *AWFP*.

the (employment-weighted) density of plants over log employment for the pooled samples. The bottom panels show this in terms of the CDF of employment over (log) plant sizes for each survey year. In all sample years, employment is more concentrated at large plants in the West. In Appendix B, we show that this difference in plant size extends back into the 1990s and is not driven by differences in urbanization between East and West Germany, nor by the assignment of Berlin to West Germany in the *SES*.

A potentially confounding factor for the East-West difference in the plant size distribution could be plant age. The restructuring of the East German economy led to the exit of many old and large plants. Figure 3 shows, however, that, even conditional on plant age, East German plants are smaller because they enter smaller and they remain smaller. Put differently, already at entry, plants in East Germany appear to choose business models that imply a relatively small plant size. What is more, the East-West difference in the employment share of large plants is essentially constant both in plant age and across entry cohorts.

Returning to Figure 2 and comparing its two top panels, one can also see that the East-West differences in the plant size distribution are not uniform across sectors. They are much stronger in the manufacturing sector, where in the West, 55% of all employees work at plants with more than 249 employees, while in the East it is only 31%. Figure 4 explores the cross-sectional heterogeneity in plant size distributions more systematically at the industry level and relates it to East-West differences in productivity and wages.

Figure 4: Productivity and wage differences and large plants by industry



Notes: The top panels relate 2014 log differences in output per worker between West and East Germany within industries to the share of employment at plants with more than 249 employees (left panels) and the standard deviation of log plant employment (right panels). Output is measured as gross value added, which is the GDP concept available at the regional level, because product-specific subsidies and taxes (the difference between the two) are only available at the national level. The lines show (VGR) employment-weighted least squares regressions. The bottom panels relate differences in mean log wages between West and East Germany within industries to the same plant size measures. The lines show (*SES*) employment-weighted least squares regressions. MFT: Food and textile manufacturing, MPW: Paper and wood manufacturing, MCP: Chemical and plastic manufacturing, MME: Metal manufacturing, MEL: Electronics manufacturing, MVE: Vehicle manufacturing, UTL: Utilities, CON: Construction, COP: Construction preparations, WHC: Wholesale and car retail, RTO: Other retail, TRA: Transportation, STO: Storage, TUR: Tourism, BAN: Banking, INS: Insurance, RNS: Research services, TES: Technical services, RES: Rental services, BAC: Building and area care, OTS: Other services, FIN: Finance. See Appendix C for the mapping of industries between the *SES* and *VGR*. Data sources: *SES* 2006/10/14 (plant sizes, wages) and *VGR* (labor productivity).

The left panels use the share of employment at plants with more than 249 employees to compare plant size distributions. The right panels use the standard deviation of log-employment instead. The employment-weighted correlation between productivity differences and plant size distribution differences (top row) is 0.53 for the 249-share and 0.44 for the standard deviation. Both top-row scatter plots show that those industries where productivity is particularly low in the East are also the industries where particularly fewer workers are employed at large plants in East Germany relative to West Germany. Relating the size distribution to output per worker has the drawback that it confounds labor share and marginal labor productivity differences between East and West Germany. To alleviate this concern, the bottom row looks at differences in average log wages. Similar to output per worker, we find that those industries where wages are particularly low in the East are also the industries where particularly fewer workers are employed at large plants in East Germany relative to West Germany. The correlations are 0.55 (249-share) and 0.49 (standard deviation), respectively.[14]

3.3 Size-Wage Nexus and Missing Large Plants

These East-West differences in the plant size distribution are, in turn, related to differences in the size-wage curves that plants face. To show this, we use the *SES* data to estimate the following reduced-form relationship between individuals' log wages, $\ln w_{it}$, and the log employment at their plant, $\ln E_{it}$:

$$\ln w_{it} = \beta_0 + \beta_E\, East_i + \hat{\omega}_W \ln E_{it} + (\hat{\omega}_E - \hat{\omega}_W)\, East_i \ln E_{it} + \beta x_{it} + e_{it}, \qquad (1)$$

where $East_i$ is a dummy equal to one when the employee's plant is in East Germany, and x_{it} are other observable plant or worker characteristics. The coefficient of interest is the difference in the size-wage slope $\hat{\omega}_E - \hat{\omega}_W$, the interaction term. In our baseline specification, we non-parametrically control for a workers' age and sex by a full set of interaction dummies and for time and industry fixed effects.

The top panel of Table 1 displays the results. It first shows that large plants pay higher average wages in both regions, as $\hat{\omega}_W, \hat{\omega}_E > 0$. Importantly, the size premium is larger in East Germany. In the West, a 1% higher employment is associated with a 0.078% higher wage. The corresponding number for the East is 0.094%, one fifth higher. For example, in West Germany, a firm with a business

[14] An additional advantage of using wages is that both the size distribution and wage measures come from the same data source (*SES*) with the same sampling procedures.

Table 1: Size-wage elasticities

	Non-primary private sector		
	Baseline	Occupation × Education	Job level × Education
Size-Wage elasticity, West, $\hat{\omega}_W$	7.8 (0.1)	6.1 (0.1)	5.5 (0.1)
Difference in elasticities, $\hat{\omega}_E - \hat{\omega}_W$	1.6 (0.3)	2.0 (0.2)	2.5 (0.2)
Implied elasticity, East, $\hat{\omega}_E$	9.4	8.1	8.0
N (in thousands)	2365	2365	2228
	Manufacturing sector		
	Baseline	Occupation × Education	Job level × Education
Size-Wage elasticity, West, $\hat{\omega}_W$	8.8 (0.2)	6.9 (0.1)	6.5 (0.1)
Difference in elasticities, $\hat{\omega}_E - \hat{\omega}_W$	4.3 (0.4)	4.9 (0.3)	5.4 (0.3)
Implied elasticity, East, $\hat{\omega}_E$	13.1	11.8	11.9
N (in thousands)	1025	1025	970

Notes: The table displays the estimated size-wage elasticities for the non-primary private (manufacturing) sector in West and East Germany. Standard errors are in parentheses. The top panel is for all workers. All coefficients are multiplied by 100 for better readability. *Baseline*: Controls for a workers' age and sex by a full set of dummy interactions, plus time, and industry fixed effects. *Occupation × Education*: Controls for a workers' age, sex, education, and occupation by a full set of dummy interactions, plus time and industry fixed effects. *Job level × Education*: Controls for a workers' age, sex, education, and job level (five levels, coding the level of autonomy, complexity, and responsibility a worker's job has, see Bayer and Kuhn, 2018) by a full set of dummy interactions, plus time and industry fixed effects. Data source: *SES* 2006/10/14.

model requiring 100 employees expects to pay 5.6% higher wages than a firm with a business model requiring 50 employees (log difference 0.69). In East Germany, the same difference in business models comes with 6.7% higher wages. Appendix D.1 shows that the result is robust to including non-linear size terms, which might otherwise drive differences in the average size-wage gradient given the differences in the plant size distributions.[15]

[15] Appendix D.1 also extends the analysis to include part-time workers and shows that this, if anything, increases East-West differences in the size-wage nexus. We also estimate a more flexible regression that allows for East/West-specific industry fixed effects and East/West-specific effects of worker characteristics (age and sex). This controls for potential East/West-differences in sorting and East/West-specific industry-level demand shocks. Again, we find that the differences in the size-wage elasticities become even a bit larger than in our baseline specification. Appendix D.3 shows that the finding of an East-West difference in the slope of the size-wage curve is also robust to using the firm size information in the *SES* 2006 sample instead of plant size.

Another concern may be that the steeper size-wage relationship in East Germany reflects large plants there attracting a larger share of high-ability workers. For this reason, we consider a second (and a third) specification where we fully interact age, sex, education, and occupation (job-level) dummies (in addition to time and industry fixed effects) to allow for plant-size-related differences in occupational (job-level) patterns within industries between East and West. The last two columns of Table 1 show that the difference between the two regions becomes yet slightly larger when we control additionally for age-, sex-, and education-specific occupational or job-level patterns.[16]

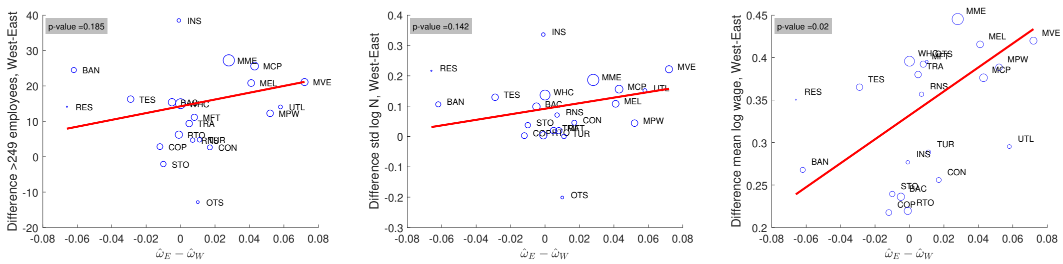
The second panel of Table 1 shows that the difference in the size-wage curve between East and West Germany is even more pronounced in the manufacturing sector. The fact that the East-West difference in the size-wage nexus is not uniform across industries generalizes. Importantly, it is also systematically related to industry variation the prevalence of large plants and average wages. To show this, we estimate Equation (1) for 21 individual industries. In the top-row panels of Figure 5, we plot the difference $\hat{\omega}_E - \hat{\omega}_W$ against (a) the difference in the share of employment at large plants, (b) the difference in the standard deviation of log employment, and (c) the difference in the average log wage for each industry. We find that the steeper the size-wage curve is in the East relative to the West, the smaller is the relative share of employment at large plants (employment-weighted correlation of 0.30). The employment-weighted correlation for the standard deviation of log plant employment is 0.33. The correlation between average wages and the size-wage nexus is with 0.52 even stronger. The steeper the size-wage curve is in an East German industry relative to its West German "twin", the more are East wages lagging behind. In Appendix E.1, we repeat everything in Figure 5 (as well as Figure 4) splitting up West German industries by four regions. The resulting correlations are similar but come with a higher degree of statistical confidence.

[16]In Appendix D.2, we investigate the issue of selection further by using the *AWFP* data, based on social security records, which allow us, with the caveat that these are top-coded earnings as opposed to hourly wage data, to use estimates of plant-level fixed effects controlling for worker fixed effects. We find the same pattern of a steeper East German size-wage curve. The *AWFP* data also has a finer spatial resolution allowing us to distinguish between metropolitan and non-metropolitan areas and to show that our results are not driven by differences in metropolitan and non-metropolitan size-wage curves.

Figure 5: The share of large plants, wages, the size-wage nexus, and collective bargaining

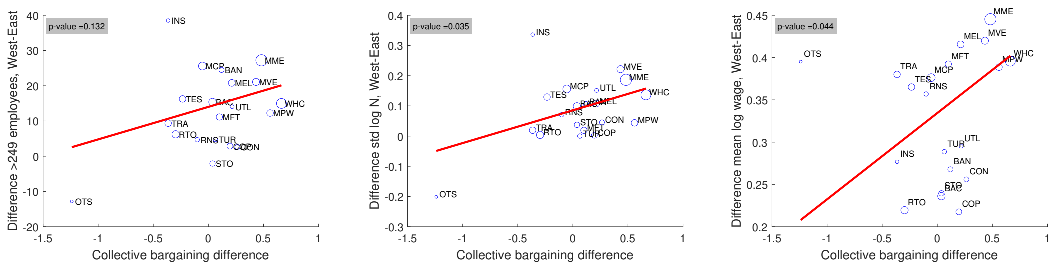
Nexus between $\hat{\omega}_E - \hat{\omega}_W$ and ...

Share of plants > 249 | Std log employment | Average log wages



Nexus between differences in the incidence of collective bargaining and ...

Share of plants > 249 | Std log employment | Average log wages



Notes: The top-row panels relate differences between West and East Germany in the share of employment at large plants, the standard deviation of log plant employment, and average log wages to differences in size-wage relationships. The bottom-row panels relate differences between West and East Germany in the share of employment at large plants, the standard deviation of log plant employment, and average log wages to the following double difference: $[\log P(C|L,E) - \log P(C|S,E)] - [\log P(C|L,W) - \log P(C|S,W)]$, where $P(C|\cdot)$ is the conditional probability of a worker being subject to collective bargaining in our sample in (L)arge (>249 employees) or (S)mall ($\leq$ 249 employees) plants in the (E)ast and (W)est. The lines show employment-weighted least square regressions. MFT: Food and textile manufacturing, MPW: Paper and wood manufacturing, MCP: Chemical and plastic manufacturing, MME: Metal manufacturing, MEL: Electronics manufacturing, MVE: Vehicle manufacturing, UTL: Utilities, CON: Construction, COP: Construction preparations, WHC: Wholesale and car retail, RTO: Other retail, TRA: Transportation, STO: Storage, TUR: Tourism, BAN: Banking, INS: Insurance, RNS: Research services, TES: Technical services, RES: Rental services, BAC: Building and area care, OTS: Other services. Data source: *SES* 2006/10/14.

3.4 Size-Wage Nexus and Collective Bargaining

What lies behind these differences in the steepness of the size-wage curves? We highlight the role of collective bargaining and the differences in the role of unions rooted in the different historical developments in the two Germanies before 1990.

In fact, the bottom panels of Figure 5 shows that our findings regarding missing large plants and lower wages by industry are also related to plant-size-specific differences in the collective bargaining incidence (CBI). On the x-axes, we show, for each industry, a double difference in the (log) incidence of collectively bargained wage contracts between large and small plants and between East and West. This double difference is then plotted against our two measures of East-West differences in the plant size distribution: the share of employment at large plants (left panel) and the standard deviation of log plant-level employment (center panel). Differences in the steepness of the size-CBI nexus are positively related to our measures of missing large plants—the employment-weighted correlations are 0.35 and 0.47, respectively. Industries in which the incidence of collectively bargained wages increases relatively more in plant size in the East are also those industries where, compared to West Germany, large plants are particularly missing in the East. Finally, the right panel relates the double difference to wage differences across industries. Industries in which the incidence of collectively bargained wages increases relatively more in plant size in East Germany are also those industries where, compared to West Germany, wages are particularly low (correlation: 0.46).

For the majority of industries, this double difference in CBI is positive. This means that the fraction of collectively bargained wage contracts increases indeed more in plant size in East than it does in West Germany. We can also see this at the worker level. The top panel of Table 2 presents estimates of linear probability, probit, and logit models for the probability that an individual worker's contract is collectively bargained. We use the same set of regressors as in our baseline size-wage regression. We find that overall the probability of collectively bargained wages increases in plant size and it does more so in East Germany.[17] In other words, union effort for collective bargaining is, in East Germany, more selectively focused on large plants.

[17] This is consistent with Table 2 in Schnabel (2005).

Table 2: Size-CBI / wage nexus

	Size-CBI nexus		
	Linear	Probit	Logit
Size-CBI coefficient, West, $\hat{\omega}_W^{\mathrm{CBI}}$	10.2 (0.3)	29.5 (1.1)	49.6 (1.9)
Difference in coefficients, $\hat{\omega}_E^{\mathrm{CBI}} - \hat{\omega}_W^{\mathrm{CBI}}$	1.0 (0.6)	6.1 (2.0)	10.7 (3.4)
N (in thousands)	2365	2365	2365
	Size-wage elasticities		
	Type of bargaining		Wage imputed
	Non-collective	Collective	using bargaining
Size-Wage elasticity, West, $\hat{\omega}_W$	7.7 (0.2)	5.8 (0.2)	0.8 (0.0)
Difference in elasticities, $\hat{\omega}_E - \hat{\omega}_W$	-0.3 (0.4)	-0.3 (0.4)	1.2 (0.2)
N (in thousands)	1378	986	2351

Notes: CBI: collective bargaining incidence. The top panel estimates the baseline regression from Table 1 replacing wages as the left-hand side by a dummy that equals one if the worker is paid according a collective bargaining contract. The first two columns of the bottom panel repeat the baseline regression from Table 1 splitting the sample by whether the worker is covered by a collective bargaining agreement or not. The last column of the bottom panel estimates the baseline regression on imputed wages, where wages are estimated regressing wages on the bargaining type, industry, year, region dummies and a full set of dummy interactions for age and sex. All coefficients are multiplied by 100 for better readability. Standard errors are in parentheses. Data source: *SES* 2006/10/14.

We view these differences in collective bargaining incidence as arising from historical developments. In the former socialist East Germany, union membership was high because non-membership was associated with economic and social disadvantages (see Hans-Böckler-Stiftung, 2022). As a result, unions were not viewed as part of civil society, as they are in West Germany, and union membership fell quickly after reunification. This union retrenchment was particularly pronounced at small plants, leaving collective bargaining concentrated at large plants.

To understand the connection between the East-West differences in size-CBI and size-wage curves better, we begin by estimating the size-wage curve separately for workers with collectively and non-collectively bargained wages, see the bottom-left panels of Table 2. We find that, once we condition on whether individual employment contracts are subject to collective bargaining, the size-wage curve in East and West Germany is basically identical.[18] First and foremost, this

[18] Collectively-bargained wages in Germany still depend on size for at least two reasons: First, unions can negotiate firm-specific wage agreements that then hold for the entire workforce of that firm. Second, the typical collective bargaining agreement establishes a wage floor for all firms bound by the agreement but allows to pay an individual worker better, e.g., through bonuses.

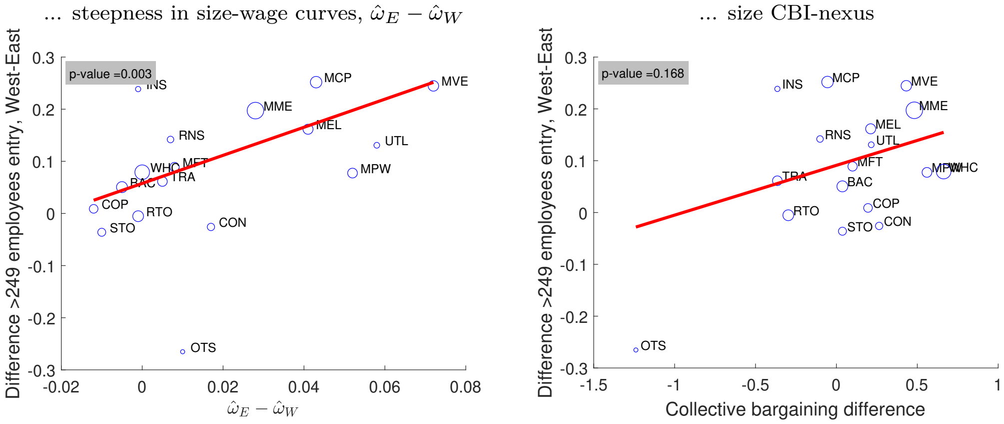
means that it must be differences in collective bargaining that drive the East-West difference in the size-wage curve.

Next, we estimate how much of the East-West difference in the size-wage elasticities is driven by the fact that collectively bargained wages are higher (and, as we have seen, the size-CBI curve is steeper in East Germany). For this purpose, we estimate a regression of real wages (in levels) on a full set of interaction dummies for sex and age, time fixed effects, industry fixed effects, and a dummy for East Germany. This is the same set of regressors as the baseline size-wage regression except for all regressors that include size. We instead include a dummy for collectively bargained wages. Importantly, there is no *direct* effect of plant size on the *predicted* individual wages from this regression. We then estimate the baseline size-wage regression using these predicted individual wages on the left hand side (after a log transformation). As this regression includes all the regressors from the prediction regression but collective bargaining, any size effect on wages must come from collective bargaining. We report this exercise in the bottom right cell of Table 2. We find that this yields an estimated size-wage elasticity difference of 1.2% compared to the 1.6% baseline estimate (see Table 1).

Beyond being higher, collectively bargained wages are also less elastic in size compared to non-collectively bargained ones (5.8 vs. 7.7 in West Germany, Table 2). This contributes, however, only approximately another 0.3% to the average East-West size-wage elasticity difference, given that East Germany has a 14% higher fraction of non-collectively bargained wages and these have a 1.9% higher elasticity ($14\% \times 1.9\% \approx 0.3\%$). In sum, the effects of collective bargaining basically explain the entire East-West difference in the size-wage elasticity.

Taken together, the data suggest that plants in East Germany face a stronger trade-off between being large and paying low wages. This stronger trade-off appears to originate from (a) collectively bargained wages being higher, and (b) a relatively larger concentration of collective bargaining at large plants in East Germany. Most importantly, across industries, the stronger size-wage trade-off in East Germany correlates with missing large plants and plants paying on average low wages.

Figure 6: Difference in employment share at entry in terms of ...



Notes: The figure displays the differences in the share of employment at large plants (more than 249 employees) within the group of plants that are at most three years old (y-axis) against (left panel) the estimated size-wage elasticity difference (x-axis) and (right panel) the difference in the incidence of collective wage bargaining between small and large plants. Data source: for employment shares: *AWFP* 2006–2014, for wage-size elasticity estimates and collective bargaining: *SES* 2006/10/14.

3.5 Size-Wage Nexus and Business Networks

The implications of monopsony power, however, do not stop with the labor market, specifically its effects on employment concentration and wages. Monopsony, by changing incentives to be large in terms of employment, also can be expected to change the incentives for choosing the scale of a firm's business model. Consistent with Figure 3 and in line with the literature (see Sedláček and Sterk, 2017), we think of this choice occurring already at entry. Another supporting fact of this view is that the relationship of the share of employment in large plants and the steepness of the size-wage / the size-CBI nexus, documented in the previous subsections, is already manifest at plant entry, as Figure 6 shows.

We further investigate this idea of size-wage curve differences affecting business model choice, exploiting the *MIP* data. Starting with a firm-level analysis, we first show that, controlling for industry and time fixed effects, firms in East Germany (i) have lower marketing expenditures, (ii) are less likely to invest in new distribution channels, (iii) have a higher share of sales with their top three customers (in terms of sales), and (iv) purchase a higher share of all their inputs from their top three suppliers (in terms of purchases), see Table 3. Taken together, (iii) and (iv) imply that East German firms have a sparser network of firms with which they interact.

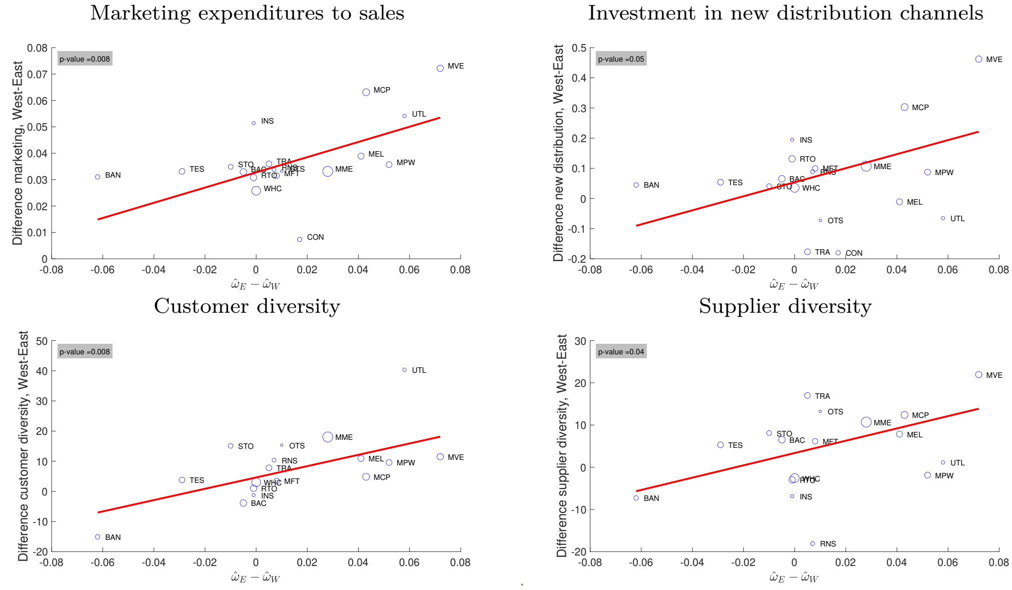
Table 3: Customer networks: difference between East and West Germany

	Marketing expenditures to sales (in %)				Investment in new distribution channels (in %)			
East Germany	-0.9	-0.7	-0.2	-0.1	-8.5	-6.2	-8.1	-11.0
	(0.2)	(0.2)	(0.2)	(0.3)	(3.1)	(3.0)	(2.6)	(3.2)
N	20455	20438	6393	1186	24071	24070	7794	1448
	Customer diversity (in %)				**Supplier diversity (in %)**			
East Germany	-10.4	-9.7	-10.2	-11.3	-5.3	-4.7	-10.7	-10.4
	(2.4)	(2.4)	(2.5)	(2.8)	(2.1)	(2.1)	(2.7)	(3.0)
N	4450	4450	1116	217	4074	4074	1050	196
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Size Controls	N	Y	Y	Y	N	Y	Y	Y
Additional controls	N	N	Y	Y	N	N	Y	Y
Only intermediate goods industries	N	N	N	Y	N	N	N	Y

Notes: The table displays the dummy coefficient for East Germany in firm-level, sales-weighted linear regressions for: (top-left) expenditures on marketing, relative to sales; (top-right) whether a firm reports to have invested in new distribution channels; (bottom-left) the share of sales that do not go to the three most important customers (in terms of sales); and (bottom-right) the share of purchases that do not come from the three most important suppliers (in terms of purchases). Data comes from the Mannheim Innovation Panel. The top panel uses the biannual data from 2006-2014, the bottom panel only from 2010. Samples based on availability of the corresponding questions. All regressions are estimated with time and industry fixed effects. Columns 2-4 control in addition for firm size. Columns 3-4 control additionally for exporting intensity, innovation expenditures, new products on the market, investment in physical capital, a dummy for government subsidies, the substitutability of one's products by products of competitors, and the wage bill relative to sales. Column 4 uses only observations from industries, which have less than 5% sales going to final-use customers (using the German input-output table). Columns 5-8 repeat this pattern.

These results are broadly robust to the inclusion of firm size and additional controls, see columns two and three in each panel. The results are also robust when we focus on industries with less than 5% of sales to final consumers in the German input-output tables, i.e., industries that produce almost exclusively intermediate goods, see column four in each panel. This addresses the potential concern that within-industry differences in customer type drive the differences between East and West Germany.

Figure 7: Customer networks and the size-wage nexus



Notes: Top-left: Expenditures on marketing, relative to sales. Top-right: Share of firms that report to have invested in new distribution channels. Bottom-left: Share of sales that do not go to the three most important customers (in terms of sales). Bottom-right: Share of purchases that do not come from the three most important suppliers (in terms of purchases). Top row: Data from the Mannheim Innovation Panel, 2006–2014 (biannual). Bottom row: Data from the Mannheim Innovation Panel, 2010. Samples based on availability of the corresponding questions. All data are sales-weighted when aggregating to the industry level. Size-wage elasticity estimates from *SES* data.

Next, we show that, at the industry level, these East-West differences are related to differences in size-wage curves, see Figure 7. We find that West German firms in industries with steeper size-wage curves in East Germany relative to West Germany have a higher marketing expenditures to sales ratio, invest more in new distribution channels, and have more diverse business networks in terms of both customer and supplier diversity. This means that firms facing a steeper size-wage trade-off have smaller-scale business models. In Appendix E.2, we show that these findings are robust to the inclusion of controls.

4 A Model of Missing Large Plants/Firms

To understand why a stronger size-wage trade-off leads to missing large plants/firms and lower aggregate productivity in East Germany, we develop a model with heterogeneous firms (to be able to capture size differences), which have labor market power (to capture the size-wage elasticities), and decide both about entry and about investment in business networks (which suggests a model of differentiated products). Since the effects of the differences in size-wage elasticities are manifest already at entry, see Figures 3 and 6 in the previous section, it is sufficient to keep the analysis in a static framework, which also provides tractability.

We will capture labor market power in the form of monopsonistic competition: A firm individually faces an upward-sloping labor supply curve despite our assumption of a fixed aggregate labor supply. As suggested by the evidence on collective bargaining from the previous section, we provide a rationalization of why size-related collective bargaining differences increase the slope of the firm's size-wage trade-off: Large firms are more likely to pay wages according to a collective bargaining agreement and these wages are higher. Thus, expected wages increase in firm size, leading to labor market power when the firm chooses its business network. Furthermore, we set up the model as a model of firms because business network decisions are usually top level. Incidentally, this is also consistent with the German institutional setting where the employer has to be a legal subject able to enter collective bargaining agreements—hence, typically a firm.

In our model, firms first decide on market entry; second, conditional on entry, they learn their technical productivity and decide on investments in their business network, think, the decision to be a small-scale or a large-scale producer. Third, firms hire labor and produce intermediate goods, which they sell to bundlers, facing both a size-wage and an output-price trade-off. We show that monopsony power affects all of these decisions. Monopsony power, as it increases profits, boosts entry of firms, but it also incentivizes each individual firm to choose smaller-scale business models. This goes beyond and amplifies the reallocation of labor from more productive to less productive firms, which is already present in models without a choice of business networks and entry (see, e.g., Berger et al., 2022). This goes also beyond the standard output loss associated with monopsony power due to underemployment, from which we abstract by assuming a fixed aggregate labor supply.

With our setup, we introduce labor market power to a Melitz (2003)-type model. There, firms have an entry decision and a decision about their exporter status. In our model, we draw on a recent and growing heterogeneous-firm literature that puts some form of customer acquisition at the center stage in addition to technical productivity differences (see Einav, Klenow, Levin, and Murciano-Goroff, 2021; Sedláček and Sterk, 2017; Gourio and Rudanko, 2014; Drozd and Nosal, 2012; Arkolakis, 2010). Therefore, our firms decide about entry and whether to enter a business relationship with a downstream bundler. Differently from the original Melitz setup, labor market power induces them not to serve all bundlers (countries in Melitz), but to decide about the size of their business network. Accordingly, firms in East Germany choose a smaller-scale business model because, in expectation, they, thus, avoid paying high collectively bargained wages.

4.1 Bundlers

There is a unit mass of bundlers indexed by j. All bundlers produce a final consumption good, Y_j, using a Dixit-Stiglitz aggregator:

$$Y_j = \left(\int_{\Omega_j} y_{ij}^{\frac{\eta-1}{\eta}} di\right)^{\frac{\eta}{\eta-1}} = \left(\int \gamma_i \theta_{ij} y_{ij}^{\frac{\eta-1}{\eta}} di\right)^{\frac{\eta}{\eta-1}}, \tag{2}$$

where, as in Melitz (2003), Ω_j is the set of varieties available to the bundler. Bundler j bundles differentiated goods, y_{ij}, from a continuum of potential intermediate good producers i (again of mass one).[19] Whether a specific bundler uses the goods from a specific producer depends on two of the business decisions outlined above: the producer must have entered and be active, $\gamma_i = 1$, and must have formed a customer relationship with the particular bundler $\theta_{ij} = 1$.

Following Melitz (2003), Appendix F.1 shows that the resulting cost-minimizing price of bundler j, the ideal price index, is given by

$$\bar{P}_j = (\Gamma\bar{\Theta})^{\frac{1}{1-\eta}} \left(\int p_{ij}^{1-\eta} di\right)^{\frac{1}{1-\eta}}, \tag{3}$$

[19] We emphasize the interaction of business network choice and labor market power in shaping firm size and productivity, and, therefore, we abstract, for tractability reasons, from how interregional trade additionally influences this nexus. We, thus, model East and West Germany as closed economies each, which is tantamount to assuming that the bundlers in both regions produce perfect substitutes. In addition, since firms in both regions, because of free entry, make zero expected profits in equilibrium, there is no incentive for firms to start up in another region.

where Γ is the mass of all active producers, $\bar{\Theta}$ is the average fraction of bundlers that an active producer sells to (and, therefore, has no j index), and thus $\Gamma\bar{\Theta}$ is the number of varieties available to bundlers. We focus on the symmetric equilibrium in which intermediate goods producers charge the same price to all bundlers, $p_{ij} = p_i$, and all bundlers are equally large, $Y_j = Y$. From this follows $\bar{P}_j = \bar{P}$.

4.2 Intermediate Good Producers

An intermediate good producer i employs $l_i\Theta_i$ workers, where Θ_i is the mass of bundlers that constitute producer i's business network, and l_i are the units of labor required to produce the representative quantity that an active producer supplies to each bundler, $y_i = z_i l_i$. That is, intermediate good producers operate a constant returns to scale production function, where z_i denotes producer i's idiosyncratic technical productivity.

4.2.1 Price-Setting to a Single Bundler and Profits

Intermediate good producers, knowing that they face monopolistic competition, post a price to any bundler they have established a network connection with ($\theta_{ij} = 1$). Hence, they set prices as a mark-up over marginal costs, given by wages w_i relative to productivity z_i:[20]

$$p_i = \frac{\eta}{\eta - 1}\frac{w_i}{z_i}. \tag{4}$$

Using this optimal price allows us to express gross profits as a function of the mass of connected bundlers and marginal costs:

$$\pi(\Theta_i, w_i) \quad = \quad \Theta_i\left(p_i y_i - w_i l_i\right) = \Theta_i\left(\frac{w_i}{z_i}\right)^{1-\eta}\left(\bar{P}\frac{\eta - 1}{\eta}\right)^{\eta}\frac{Y}{\eta - 1}. \tag{5}$$

Importantly, gross profits for a given wage are linear in the mass of bundlers in the firm's business network. However, an intermediate good producer's wage is increasing in its total number of employees, i.e., it faces monopsonistic competition in the labor market.

[20]The intermediate good producers' price-setting can ignore the fact that they are in monopsonistic competition in the labor market, as each bundler is infinitesimally small and, hence, a marginal increase in the quantity sold to a single bundler has only a second-order impact on the producer's total labor demand and is, thus, irrelevant for the producer's first-order condition.

4.2.2 Modeling Monopsony Power in the Labor Market

As in our empirical specification in Equation (1), we assume the wage-size relation to have a constant elasticity:

$$w_i = \left(\frac{l_i \Theta_i}{\bar{l}\bar{\Theta}}\right)^{\hat{\omega}} W, \tag{6}$$

where we express size relative to the average producer size in the economy, $\bar{l}\bar{\Theta}$, and W is a wage index, which we set to 1, making labor the numeraire.

The following is a simple rationalization of this formulation as a first-order approximation which permits tractability: Along the lines of our empirical exercises regarding collective bargaining, assume a firm has to pay an individual worker according to a collective bargaining agreement with probability $p_{coll} = p_0 + p_1 \ln\left(\frac{l_i \Theta_i}{\bar{l}\bar{\Theta}}\right)$.[21] Further, firms expect to pay a multiplicative wage premium of τ over the non-collective wage $\tilde{W}$. This means that a firm *expects* to pay

$$\ln \mathbb{E} w_i = \ln\left[\left((1+\tau)p_{coll} + (1-p_{coll})\right)\tilde{W}\right] = \ln\left[(1+\tau p_{coll})\tilde{W}\right] \approx \tau p_{coll} + \ln \tilde{W}$$

as its average wage. Lastly, we allow for the non-collectively bargained wage to be directly size-dependent for reasons such as preferences for specific workplaces (see, e.g., Berger et al., 2022) or imperfect information about outside options (see, e.g., Jäger, Roth, Roussille, and Schoefer, 2024) and, thus, specify $\tilde{W} = \hat{W}\left(\frac{l_i \Theta_i}{\bar{l}\bar{\Theta}}\right)^{\xi}$.

Plugging in for p_{coll} and $\tilde{W}$ and rearranging, we then obtain for the wage that a firm expects to pay when deciding about their business model

$$\mathbb{E} w_i = \hat{W} \exp(\tau p_0) \left(\frac{l_i \Theta_i}{\bar{l}\bar{\Theta}}\right)^{\tau p_1 + \xi}.$$

This is the functional form of Equation (6). It gives an interpretation to $\hat{\omega}$ as the product of the collective bargaining wage premium, τ, and the semi-elasticity of p_{coll} on firm size, p_1, plus a term unrelated to collective bargaining, ξ. In line with our empirical results, see bottom left of Table 2, we assume the latter is constant

[21] It is well known that the linear probability model is a good approximation to the logit/probit model for probabilities in the range of 0.1 and 0.9. We have tested whether employment size should enter in logs or in levels and found that the log-formulation achieves a substantially higher likelihood in both the probit and logit estimate.

across regions, i.e., regional differences in $\hat{\omega}$ reflect regional differences in collective bargaining. Given this rationalization, we now proceed with Equation (6).

4.2.3 Choosing the Business Network

The intermediate good producer maximizes gross profits net of investments in the business network but takes into account that wages are a function of the total number of employees. To connect with one additional bundler, the intermediate good producer has to invest $\mu\bar{P}$ (μ measures costs in terms of the output good). One example for such costs would be the costs of marketing. The resulting operating profits are:

$$\Pi_i(\Theta_i) = \pi(\Theta_i, w_i(\Theta_i)) - \mu\bar{P}\Theta_i. \tag{7}$$

where we use the fact that we can express wages as a function of the mass of bundlers in firm i's network. Using the price setting equation and the production function, we obtain, summarizing aggregate terms in $\bar{w}$ (see Appendix F.2) the following functional form:

$$w_i(\Theta_i) = z_i^{\frac{(\eta-1)\hat{\omega}}{1+\eta\hat{\omega}}}\bar{w}\left(\frac{\Theta_i}{\bar{\Theta}}\right)^{\frac{\hat{\omega}}{1+\eta\hat{\omega}}}. \tag{8}$$

Equation (7) together with (5) shows that profits depended linearly on the size of the business network Θ_i if it was not for monopsony power in the labor market. Therefore, it is monopsony power in the labor market that implies an interior solution to the optimal business model choice. Appendix F.2 shows that we can write the resulting first-order condition as

$$\frac{\Theta_i}{\bar{\Theta}} = z_i^{\frac{1+\hat{\omega}}{\hat{\omega}}}\left[\frac{1+\hat{\omega}}{1+\eta\hat{\omega}}\frac{Y}{\mu}\frac{1}{\eta}\left(\frac{\bar{P}}{\bar{w}}\frac{\eta-1}{\eta}\right)^{\eta-1}\right]^{\frac{1+\eta\hat{\omega}}{\hat{\omega}(\eta-1)}}. \tag{9}$$

This equation relates the optimal amount of connected bundlers to a producer's idiosyncratic productivity, z_i. More productive producers find it optimal to create a larger business network, but the steepness of the size-wage curve, $\hat{\omega}$, moderates this relationship. A yet different way to think about the producers' optimal business network decision is to use (8) and express (9) in terms of the real wage paid by a producer:

$$\frac{w_i}{\bar{P}} = \left[\frac{1+\hat{\omega}}{1+\eta\hat{\omega}}\frac{Y}{\mu}\frac{1}{\eta}\right]^{\frac{1}{\eta-1}}\frac{\eta-1}{\eta}z_i. \tag{10}$$

The real wage is proportional to idiosyncratic technical productivity, z_i, which also implies that marginal costs, $\frac{w_i}{z_i}$, and hence prices, are constant across producers. Owing to producers' product market power, workers do not receive the full marginal product of labor. Instead, they get a wage equal to the technical productivity multiplied by the inverse mark-up in the product market, $\frac{\eta-1}{\eta}$, and by the term in squared brackets, which reflects the efficiency of the producer's network. The producer chooses a larger and, hence, more efficient network, if profits in one market (in goods), i.e., Y multiplied by the profit margin $\frac{1}{\eta}$, relative to the costs (in goods) of serving one more market, μ, are higher. In addition, in this choice, producers take into account the effect of their workforce size on their wages and, hence, their operating profits. This effect becomes stronger when the size-wage trade-off becomes steeper as captured by the elasticity $\frac{1+\hat{\omega}}{1+\eta\hat{\omega}} < 1$, decreasing the network size.

Appendix F.2 also shows how aggregating the individual business network choice in Equation (9) leads to an expression for the average network size:

$$\bar{\Theta} = \frac{Y/\Gamma}{\mu}\frac{1}{\eta}\frac{1+\hat{\omega}}{1+\eta\hat{\omega}}. \tag{11}$$

Importantly, the average network size depends negatively on the size-wage elasticity, $\hat{\omega}$, as higher monopsony power discourages investments in business networks, in line with the data (see Figure 7).[22] It depends positively on the market size per producer acquired by one unit of business network investment spending, $\frac{Y/\Gamma}{\mu}$.

To derive a closed-form solution for the distribution of optimal business network choices, we need to make a distributional assumption about idiosyncratic productivity, z_i. We assume that z_i is log-normally distributed, $z_i \sim LN(\ln \bar{z}, \Sigma^2)$ and define $\phi = \exp\left(\frac{1}{2}\Sigma^2\right)$, such that average productivity is $\bar{z}\phi$.[23]

[22]Note that Figure 7 displays positive relationships because the y-axis uses West-East and the x-axis East-West differences.

[23]Later we show that the plant size distributions in East and West Germany are well approximated by our model assuming a log-normal productivity distribution. Strictly speaking, we approximate the solution, ignoring the upper bound on Θ_i. The support of the log-normal distribution of z_i has no upper bound and, hence, there are always some firms for which (9) produces a $\Theta_i > 1$. However, in our calibration, that fraction is negligible.

This distributional assumption allows us to to express individual business network choices, (9), as a function of z_i, labor market power, and distributional parameters (see Appendix F.3 for details):

$$\frac{\Theta_i}{\bar{\Theta}} = \left(\frac{z_i}{\bar{z}\phi}\phi^{-\frac{1}{\hat{\omega}}}\right)^{\frac{1+\hat{\omega}}{\hat{\omega}}}. \tag{12}$$

This equation highlights that the more a producer's productivity exceeds average productivity ($z_i > \bar{z}\phi$), the larger is its business network relative to the average. What is more, the increase is more than proportional because $\frac{1+\hat{\omega}}{\hat{\omega}} > 1$. This inequality is also the reason that $\log \Theta_i$, which is also normally distributed, has a larger variance than $\log z_i$. This means that the distribution of business networks, the distribution of Θ_i, is more right-skewed than the productivity distribution: The most productive producers build particularly large networks. The endogenous business network choice amplifies, therefore, productivity heterogeneity. This amplification becomes smaller as $\hat{\omega}$ increases: A stronger size-wage trade-off renders the acquisition of additional customers less attractive because wages rise faster.

Before we turn to the final intermediate producer decision, namely entry, we point out two properties of the optimal producer size. First, expressing l_i also as a function of z_i and combining it with (12), yields overall producer size as a function of individual productivity and aggregates (see Appendix F.3):

$$l_i\Theta_i = z_i^{1/\hat{\omega}} Y (\Gamma\bar{\Theta})^{\frac{\eta}{1-\eta}} \bar{\Theta} \left(\frac{1}{\bar{z}\phi}\phi^{-\frac{1}{\hat{\omega}}}\right)^{\frac{1+\hat{\omega}}{\hat{\omega}}}. \tag{13}$$

From this equation follows immediately that producer size is increasing in idiosyncratic productivity.

Second, from (13), we obtain an explicit solution for the standard deviation of log producer employment:

$$std\left(\log(l_i\Theta_i)\right) = std\left(\frac{1}{\hat{\omega}}\log z_i\right) = \frac{1}{\hat{\omega}}\Sigma. \tag{14}$$

That is, the distribution of log producer employment is, similarly to the distribution of business networks, normally distributed. Its dispersion depends positively on the standard deviation of idiosyncratic productivity, Σ. Importantly, and consistent with the data in Figure 5, it depends negatively on the size-wage elasticity.[24]

4.2.4 Producer Entry

We assume free producer entry which implies that competition drives average producer profits to zero. Denoting with $\lambda\bar{P}$ (λ is measured again in terms of the output good) the costs to establish a producer, the zero profit condition reads

$$\int \Theta_i y_i \left(p_i - \frac{w_i}{z_i}\right) di - \int \mu\bar{P}\Theta_i di = \lambda\bar{P}, \tag{15}$$

for given business model choices and price setting, where we use that producers learn their idiosyncratic productivity level, z_i, only after entry.

The gross profits per unit of goods sold (in terms of goods) are constant in every market and equal to $1/\eta$. Therefore, the expected gross profits are this profit margin times the average goods sold per producer which is Y/Γ. This implies that the zero-profit condition simplifies to

$$\frac{Y}{\Gamma}\frac{1}{\eta} = \lambda + \mu\bar{\Theta}, \tag{16}$$

which equalizes expected gross profits with the entry costs, λ, plus average business network investment costs, $\mu\bar{\Theta}$.

4.3 Equilibrium

In equilibrium, the total amount of employment needs to equal aggregate labor supply, which we fix at one unit.[25] Hence, labor demand of all active producers, (13), integrated over all producers needs to be one:

[24]Specifically, we refer to the middle-upper panel in Figure 5. Note that Figure 5 displays positive relationships because the y-axis uses West-East and the x-axis East-West differences.

[25]Assuming that the cost of business network creation, μ, the cost of increasing the share of connected customer-bundlers by one unit, scales with population size makes this an innocuous normalization even though the economy features an aggregate demand externality, as we show below.

$$\Gamma \int l_i \Theta_i di = \Gamma \int z_i^{\frac{1}{\hat{\omega}}} Y (\Gamma\bar{\Theta})^{\eta/(1-\eta)} \bar{\Theta} \left(\frac{1}{\bar{z}\phi} \phi^{-\frac{1}{\hat{\omega}}} \right)^{\frac{1+\hat{\omega}}{\hat{\omega}}} di = 1 \tag{17}$$

which, solving for Y, yields:

$$Y = \bar{z}\phi (\Gamma\bar{\Theta})^{\frac{1}{\eta-1}} \phi^{\frac{2}{\hat{\omega}}}. \tag{18}$$

This equation highlights two key properties of the model: First, aggregate output increases not only with expected technical productivity, $\bar{z}\phi$, but also in the mass of intermediate good producers connected with the representative bundler, $\Gamma\bar{\Theta}$. This network size effect is important because of love-of-variety at the level of the bundlers. It reflects the fact that a larger variety of intermediate inputs used by the final good bundlers increases their efficiency. Second, the last term, $\phi^{\frac{2}{\hat{\omega}}}$, is a labor allocation effect similar to the Oi-Hartman-Abel effect (see Oi, 1961; Hartman, 1972; Abel, 1983). It arises through the complementarity of labor and technical productivity, z_i. This complementarity can be exploited better when a low $\hat{\omega}$ allows for a higher concentration of labor at the most productive producers.

Ultimately, Equation (18) together with the average network size, (11), and producer entry, (16), determine the aggregate equilibrium in the economy. Normalizing average producer productivity $\bar{z}\phi$ to one and solving these equations for aggregate output, the average mass of connected bundlers, and the share of active producers yields:

$$Y = \left(\frac{1}{\mu\eta} \frac{1+\hat{\omega}}{1+\eta\hat{\omega}} \right)^{\frac{1}{\eta-2}} \left(\phi^{\frac{2}{\hat{\omega}}} \right)^{\frac{1}{\eta-2}} \phi^{\frac{2}{\hat{\omega}}}, \tag{19}$$

$$\bar{\Theta} = \frac{\lambda}{\mu} \left[\frac{1}{\eta-1} \left(\frac{1+\hat{\omega}}{\hat{\omega}} \right) \right], \tag{20}$$

$$\Gamma = \frac{1}{\lambda} \frac{\eta-1}{\eta} \frac{\hat{\omega}}{1+\eta\hat{\omega}} Y. \tag{21}$$

Equation (19) shows that output is the product of three terms, which are all negatively affected by the size-wage trade-off. The last term, $\phi^{\frac{2}{\hat{\omega}}}$, is the aforementioned labor allocation effect on output that would also be present in a pure monopsony model with heterogeneous producers but without endogenous customer acquisition (and without product market power), as we show in Appendix G.[26] In other words, there is an output loss because labor market power leads to insufficient employment at large, productive firms.

Dividing (18) by (19) (and taking into account the normalization of productivity $\bar{z}\phi = 1$) yields a convenient interpretation of the first two terms of the right hand side of (19): They reflect the efficiency of the transformation of intermediate goods into final goods, a love-of-variety effect. This efficiency depends on $\Gamma\bar{\Theta} = \left(\frac{1}{\mu\eta}\frac{1+\hat{\omega}}{1+\eta\hat{\omega}}\right)^{\frac{\eta-1}{\eta-2}}\left(\phi^{\frac{2}{\hat{\omega}}}\right)^{\frac{\eta-1}{\eta-2}}$, the number of varieties available to bundlers, which is negatively affected by monoposony power. The first term, $\left(\frac{1}{\mu\eta}\frac{1+\hat{\omega}}{1+\eta\hat{\omega}}\right)$, reflects the fact that all producers reduce their business network size because of their monopsony power. This term would also be present in a model without producer heterogeneity, $\phi = 1$. The second term, $\phi^{\frac{2}{\hat{\omega}}}$, reflects the fact that it is particularly harmful that the most productive producers reduce their network size. The fact that both terms enter the average network size with an exponent, $\frac{\eta-1}{\eta-2}$, larger than one, reflects that there is a demand externality in the model, which can also be seen in (21): When aggregate demand is high, more producers enter, the number of varieties increases and the economy becomes more productive. In turn, output increases further and, hence, also demand.[27] Turning now to Equations (20) and (21), we see that monopsony power in the labor market decreases the size of business networks, $\bar{\Theta}$, and increases entry, Γ, given Y. The latter effect should not come as a surprise because monopsony power leads to higher profits, which incentivize entry. Importantly, however, the product of the two, the total number of available varieties and, therefore, the efficiency of the economy is negatively affected by $\hat{\omega}$. The effect on business network investments dominates. As a result,

[26] Whether one interprets the impact of $\hat{\omega}$ on the allocation of labor across differently productive producers—through $\phi^{\frac{2}{\hat{\omega}}}$—as an inefficiency depends on the ultimate source of $\hat{\omega}$. We have discussed some potential sources in Section 4.2.2. Given the positive focus of this paper, we ultimately do not need to take a stance on this question.

[27] This demand externality is one important difference to Kroft, Luo, Mogstad, and Setzler (2020), who discuss the effects of simultaneous labor market and product market power in a model in which each producer serves only a single product market. They find that product and labor market power dampen each other. The demand externality implies that an increase in product market power, which comes with an increase in love of variety, makes the distortions of the production network size that come from labor market power more detrimental in our model.

in an economy with large monopsony power in the labor market, there are fewer varieties available, and the varieties available originate more from entry as opposed to business investments. This means that, in such an economy, the typical entrant is small.

Perhaps surprisingly, the equations also show that the total number of varieties, $\Gamma\bar{\Theta}$, does not depend on the entry costs λ. Higher entry costs reduce producer entry. However, they increase the average output per producer, Y/Γ, see Equation (21), and thus incentivize business network investments, see Equation (11). By contrast, business network costs, μ, do affect negatively the total number of varieties as just highlighted. We discuss this further in Section 5.2.1.

From Equations (19) to (21), it also follows that aggregate labor compensation measured in final goods, which equals aggregate output minus entry and marketing costs, is proportional to aggregate output, where the proportionality factor is the inverse markup:

$$LC = Y - \Gamma(\lambda + \mu\bar{\Theta}) = Y\left[1 - \left(\frac{\eta-1}{\eta}\frac{\hat{\omega}}{1+\eta\hat{\omega}} + \frac{1}{\eta}\frac{1+\hat{\omega}}{1+\eta\hat{\omega}}\right)\right] = Y\frac{\eta-1}{\eta}. \quad (22)$$

This means that it is irrelevant whether we compare Y or LC differences across regions in what follows (assuming η is the same).

5 Model Implications

Using this model, we now quantify the implications of the differences in monopsony power between East and West Germany that we documented in Section 3, in particular those for aggregate productivity. Moreover, we provide additional cross-sectional and time-series evidence supporting the model's main mechanism.

5.1 East-West Productivity and Size Differences

The model contains five parameters, only three of which matter for the comparison of East and West German aggregate labor productivity: The degree of labor market power, $\hat{\omega}$, the degree of product market power, η, and the standard deviation of idiosyncratic technical productivity, Σ.

Table 4: Size distortions and output losses: model vs. data

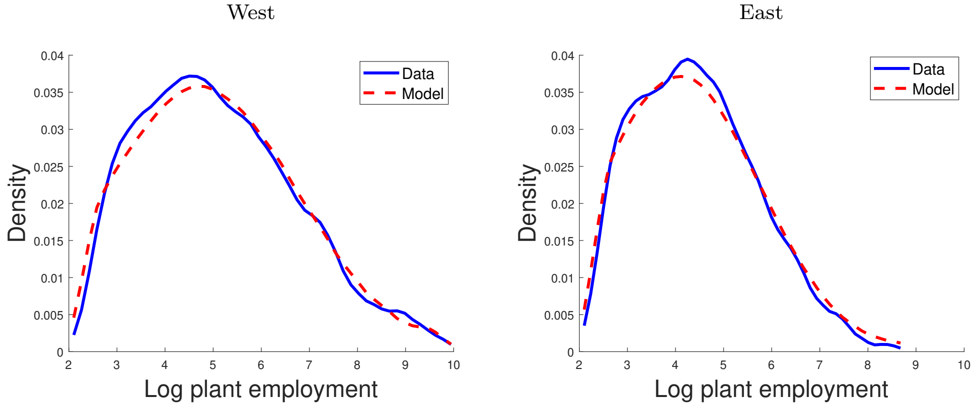
Variable	Model West	Model East	Data West	Data East
	Private non-primary sector $\hat{\omega}_W = 0.078$ and $\hat{\omega}_E = 0.094$			
$1/\Gamma$	**61.4**	44.6	**61.4**	46.4
Share E > 249	**0.39**	0.22	**0.39**	0.21
Y_{east}/Y_{west}	0.90		0.74	
	Manufacturing sector $\hat{\omega}_W = 0.088$ and $\hat{\omega}_E = 0.131$			
$1/\Gamma$	**98.5**	57.1	**98.5**	64.2
Share E > 249	**0.55**	0.24	**0.55**	0.31
Y_{east}/Y_{west}	0.84		0.70	

Notes: The table compares model simulated moments to data moments from the *SES* (pooled 2006/10/14) and German national accounts for the private, non-primary sector (top panel) and manufacturing (bottom panel). $1/\Gamma$: Average plant size, *Share* $E > 249$: Share of employment at plants with more than 249 employees. Bold numbers are calibrated/calibration targets. Y_{east}/Y_{west}: Output per worker in East relative to West Germany.

To isolate and quantify the effect of a steeper size-wage trade-off in East Germany, our calibration strategy is to set all parameters in East and West Germany to the same value except for labor market power. For $\hat{\omega}$, we use our baseline estimates ($\hat{\omega}_W = 0.078$, $\hat{\omega}_E = 0.094$) from Section 3.3. Bundesbank (2017) finds an average price-cost margin of 1.4 in Germany, and, therefore, we set $\eta = 3.5$. Finally, we calibrate the standard deviation of idiosyncratic log technical productivity, Σ (0.16), to match the share of employment in West German large plants.

The business network investment costs, μ, and entry costs, λ, are irrelevant for the *relative* productivity question. Therefore, we simply pick μ (25) such that the average business network is small ($\bar{\Theta} = 0.01$) and virtually no firm is connected to all bundlers. Given this choice, we calibrate λ (0.05) to match the average West German plant size (61 employees) in the data, i.e., we interpret the plant data as coming from single-plant firms. This notion of plant size allows us to impose a truncation at ten employees in the model simulation in line with the truncation in the data. We use this truncated numerical simulation whenever we evaluate the

Figure 8: Plant size distribution: model vs. data



Notes: The figures display the empirical employment-weighted plant size distributions (blue solid lines) for East and West Germany as well as simulations of the plant size distribution from our structural model (dashed red lines). Actual and simulated distributions are estimated using a Gaussian kernel smoother. Data source *SES* 2006/10/14, private non-primary sector.

model's plant size distribution against the empirical one. However, we compute aggregate productivity in the model following the closed-form solution (19), i.e., using the non-truncated producer distribution, when we compare it to national accounts data that is based on the universe of producers.

The top panel of Table 4 displays the results of this exercise. First and importantly, by varying only $\hat{\omega}$, the model matches the moments of the plant size distribution (that were targeted for West Germany) extremely well also in East Germany where they were not targeted. That is, the average firm/plant size decreases from 61 to 45 employees compared to 46 in the data, and the share of workers employed at large firms/plants decreases from 39 to 22 percent compared to 21 percent in the data. As Figure 8 shows, this tight match of model and data in both East and West Germany extends to the entire employment-weighted plant size distribution, despite the fact that only two moments of the West German distribution are targeted.

Second, the model, through these effects of $\hat{\omega}$ on the firm size distribution, implies a substantial drop in productivity by ten percentage points. In other words, the model explains roughly 40 percent of the observed output differences per worker between the two regions. From Equation (22), it follows that the model also rationalizes a ten percentage points lower labor compensation in East relative to West Germany.

Table 5: Decomposition of output losses

	Private non-primary	Manufacturing
Total productivity difference	10.3%	15.5%
Business network size effect, $(\Gamma\bar{\Theta})^{\frac{1}{\eta-1}}$	5.4%	5.6%
sans heterogeneity, $\left(\frac{1}{\mu\eta}\frac{1+\hat{\omega}}{1+\eta\hat{\omega}}\right)^{\frac{1}{\eta-2}}$	1.9%	2.9%
cum heterogeneity, $\phi^{\frac{2}{\hat{\omega}}\frac{1}{\eta-2}}$	3.5%	2.7%
Labor allocation effect, $\phi^{\frac{2}{\hat{\omega}}}$	5.2%	10.6%

Notes: The table displays the output losses per worker in East relative to West Germany, $1 - Y_{east}/Y_{west}$ from Table 4, decomposed, to the first order, into the three channels highlighted in the discussion of Equation (19).

Section 3.3 shows that East-West size and productivity differences are particularly large in manufacturing. To investigate whether the model is able to match this stylized fact, we next, keeping the general calibration strategy the same, recalibrate our economy to the manufacturing sector in West Germany. The bottom panel of Table 4 shows that the average plant size in manufacturing is larger than in the total private, non-primary sector and that a larger share of workers is employed at large plants. Accordingly, we adjust the dispersion of idiosyncratic productivity, Σ (0.17), and entry costs, λ (0.82). Bundesbank (2017) finds that average price-cost margins in manufacturing are lower than in the private sector as a whole, implying $\eta = 6$.

The bottom panel of Table 4 shows that also for the manufacturing sector the difference in the size-wage trade-off alone is able to explain the smaller average plant size and the lower share of employment at large plants in East Germany. Importantly, and consistent with the data, the model produces output differences in manufacturing that are larger than in the private sector as a whole. The model predicts that output in East Germany is 84 percent of output in West Germany, in the data it is 70 percent.

Table 5 decomposes the predicted output losses into the two channels we have highlighted in Equation (19). In the private, non-primary sector, the total output effect is split roughly half into the business network size and the labor allocation effect. In manufacturing, the share of the effects is roughly one third and two thirds, respectively.

Of the two terms that constitute the business network size effect, in the private non-primary sector, the term arising from heterogeneity is quantitatively larger than the effect that would also be present in a homogeneous producer model. In other words, the model implies that monopsony power is particularly costly when it discourages the most productive producers to choose a business model with many customers, rendering the business networks in the economy less efficient. In the manufacturing sector, the split is more even.

5.2 Discussion of Additional Model Implications

5.2.1 Wages, Business Network Investment Costs, and Consumption

In this subsection, we explore whether introducing wedges in the firm's decision problem can change output net of resources spent on entry and investment in business networks. Within the limitations of our model, we can think of this as aggregate consumption, C:

$$C := Y - \Gamma(\lambda + \mu\bar{\Theta}). \tag{23}$$

We establish two properties of the model: We begin by arguing that introducing a wedge on wages, intended to change a firm's incentive to hire has no effect on consumption. For the sake of concreteness, think of a wage subsidy. Intuitively, such a subsidy raises the labor demand of all producers but neither change the relative distortions of labor demand nor create incentives to invest in larger business networks. Wages go up one for one with the subsidy, this leaves profits unaltered, so that also entry does not change. With fixed aggregate labor supply, constant aggregate consumption follows. Appendix H contains the formal argument.

Next, introducing a wedge on business network investments, intended to increase a firm's incentive to create larger business networks, can increase consumption. The intuition for this result is that, first, product market power implies that the social resource cost of investing in business networks is smaller than the private resource cost, which includes the markup. Second, privately, the firm takes into account that larger networks require a larger workforce, which raises wages, when deciding about its business network investments. Yet, these private costs of higher wages are not social resource costs. As a result, a negative wedge, "a subsidy," on business investment can increase aggregate consumption because larger networks that render all producers more productive (in terms of the final good) create a positive externality by making more varieties available to bundlers. Appendix I formalizes this argument. It shows that there is a consumption-maximizing positive "subsidy", which also increases the number of active firms. This means that even in a setup where households have preferences not only over consumption but also over the number of employers they can work for (like in the monopsony model of Berger et al., 2022), these households should prefer such a subsidy.[28] Yet, as Appendix I also shows that such a subsidy can only ameliorate the business network size effect *sans* heterogeneity (as defined in Table 5).

5.2.2 Sales per Worker

Thus far, we have studied the predictions of the model with respect to aggregate productivity differences. However, our model also has a strong prediction in terms of firm-level revenue productivity of labor: Its elasticity with respect to the total workforce equals $\hat{\omega}$. To see this, we note that the total sales of a firm are $p_i y_i \Theta_i$ and the total workforce is $l_i \Theta_i$. Using equation (3) and recalling that all firms charge the same price, we obtain that real sales per worker

$$\frac{\frac{p_i}{\bar{P}} y_i \Theta_i}{l_i \Theta_i} = \frac{p_i}{\bar{P}} z_i = (\Gamma \bar{\Theta})^{\frac{1}{\eta - 1}} z_i \tag{24}$$

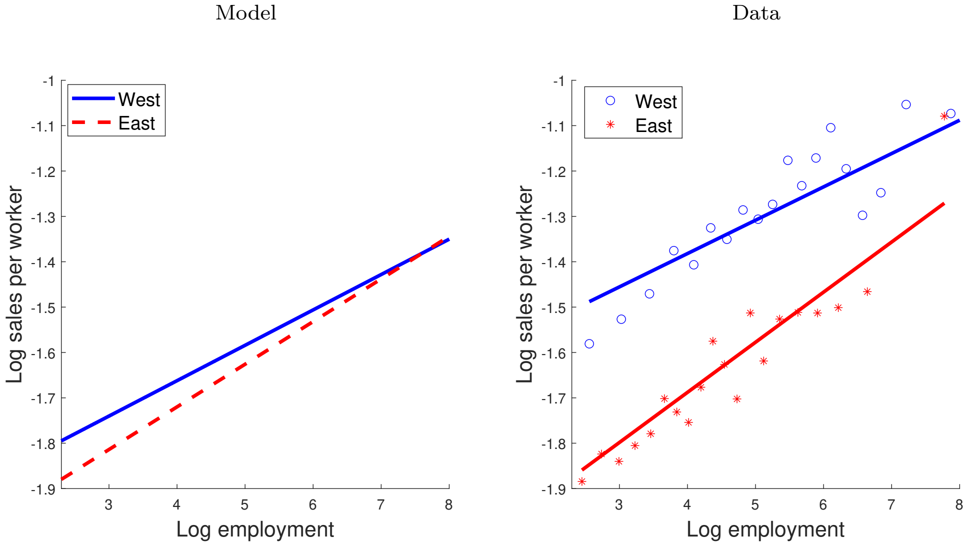
is proportional to technical productivity. At the same time, we obtain from (13) that the number of employees,

$$\bar{\kappa}(l_i \Theta_i)^{\hat{\omega}} = z_i \tag{25}$$

is log-linear in productivity, where $\bar{\kappa}$ is an aggregate shifter (that captures aggregate productivity). Combining both gives the stated result.

[28] In our calibration, the output-net-of-cost maximizing "subsidy" would be 37% in West Germany and would increase output net of costs by 9%. Owing to the steeper size-wage curve, the optimal subsidy is slightly larger in East Germany (38%) and the output gain (again net of costs) would be 10%.

Figure 9: Firm size and sales per worker



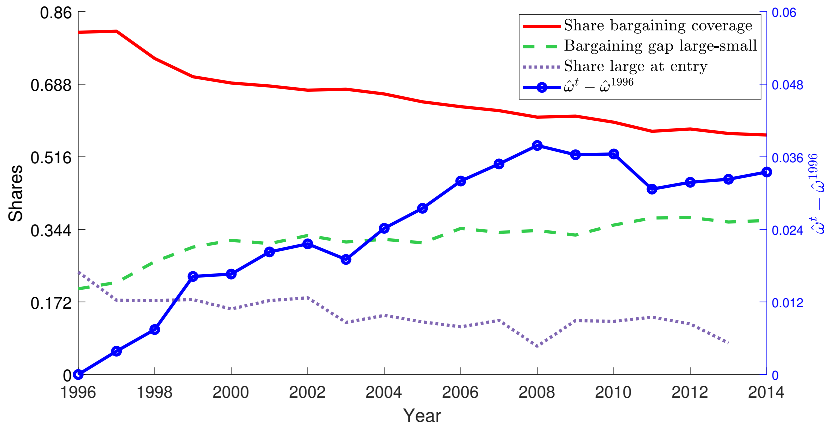
Notes: The figure shows the log sales per worker plotted against log employment. The left panel shows the relationship in our model (baseline calibration), the right panel shows a binscatter plot from the ZEW Mannheim Innovation Panel (2006-2014) together with linear regressions. Data are weighted by the square root of employment to capture precision. We adjust the aggregate price level (unit of account) in the model to match the empirical log-sales per worker of the East German firms with a workforce of 10 workers.

The MIP data contains both total employment and sales of firms and, thus, allows us to test this prediction, operationalizing the revenue product of labor as sales per worker. Figure 9 plots the relationship for the model (left panel) alongside a binscatter plot and linear regressions for the data (right panel). We find: (i) the log-relationship is a good fit, and (ii) the slope is steeper for East Germany, also as predicted, and (iii) the slopes in the data and in the model are of comparable magnitudes. In the data, the East and West German curves are further apart than in the model. This ultimately corresponds to the residual aggregate productivity difference between East and West Germany that our model cannot explain.

5.2.3 Time-Series Evidence

We, next, provide further suggestive evidence from the *AWFP* for the basic model mechanism, now from the time series, see Figure 10. We use similar statistics as in our earlier micro and cross-sectional evidence in Section 3. First, the figure shows

Figure 10: Large plants, steepness of the size-wage curve, and collective bargaining over time



Notes: On the left axis, the figure displays for all of Germany, private non-primary sector, over time and employment-weighted the share of workers covered by a collective bargaining agreement (share bargaining coverage), the difference in the probability to be covered by collective bargaining for workers at plants with at least 250 employees relative to workers at plants with fewer employees (Bargaining gap), and the share of employment at plants of at least 250 employees in an entering cohort of plants, four quarters after entry (share large at entry). On the right axis, it displays the steepness of the size-wage curve minus its steepness in 1996 ($\hat{\omega}^t - \hat{\omega}^{1996}$). Data sources: *AWFP* for $\hat{\omega}^t - \hat{\omega}^{1996}$ and "share large entry" and *IAB Establishment Panel*, for "Share bargaining coverage" and "Bargaining gap".

that, in Germany as a whole, the fraction of workers covered by collective bargaining agreements has substantially declined over time, 24 percentage points between 1996 and 2014. What is more, collective bargaining declined foremost at small plants (for evidence on size-dependent retrenchment in collective bargaining see also Jäger et al., 2022).[29] In 1996, workers at plants with more than 249 employees had a 20% higher probability to be covered by collective bargaining compared to workers at plants with fewer employees. This gap rose to 37 percentage points by 2014. Second, and in line with our cross-sectional evidence, this selective decline in collective bargaining goes along with a Germany-wide steepening of the

[29]In an influential study, Brown and Medoff (1978) show that, at the industry level in the U.S., high unionization rates are positively associated with labor productivity. Subsequent studies fail to confirm this earlier finding using within-industry, firm-level data (see Hirsch, 2004, for a survey). Our analysis suggests that these results may not be contradictory. At an aggregate (industry) level, an increase in unionization of small plants flattens ex-ante size-wage curves, making it more attractive to choose productivity-enhancing large-scale business models. This raises aggregate labor productivity. However, given that the threat of unionization affects business model choices at entry, productivity differences need not manifest themselves when individual unionized and non-unionized firms are compared within industry.

Table 6: Size-wage elasticities: *SES* 2018

	Non-primary private sector		
	Baseline	Occupation × Education	Job level × Education
Size-Wage elasticity, West, $\hat{\omega}_W$	8.9 (0.2)	7.0 (0.1)	6.2 (0.2)
Difference in elasticities, $\hat{\omega}_E - \hat{\omega}_W$	-0.5 (0.4)	0.3 (0.4)	1.0 (0.4)
Implied elasticity, East, $\hat{\omega}_E$	8.4	7.3	7.2
N (in thousands)	357	357	340

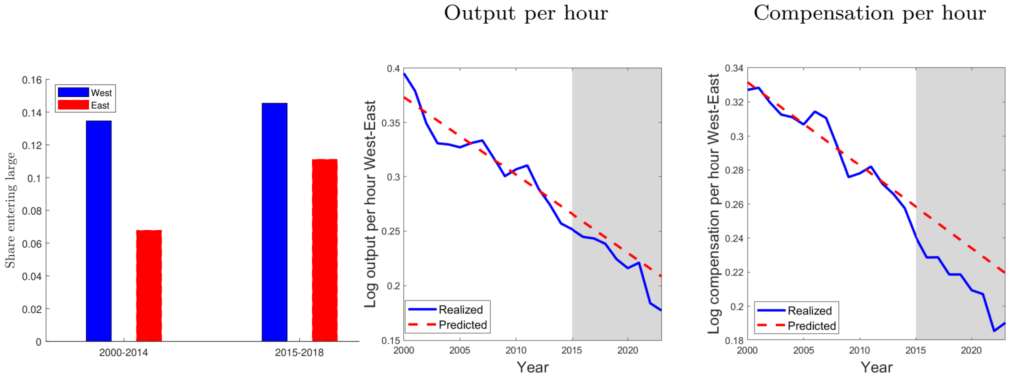
Notes: The table displays the estimated size-wage elasticities for the non-primary private sector in West and East Germany in 2018. Standard errors are in parentheses. All coefficients are multiplied by 100 for better readability. *Baseline*: Controls for a workers' age and sex by a full set of dummy interactions, plus time, and industry fixed effects. *Occupation* × *Education*: Controls for a workers' age, sex, education, and occupation by a full set of dummy interactions, plus time and industry fixed effects. *Job level* × *Education*: Controls for a workers' age, sex, education, and job level (five levels, coding the level of autonomy, complexity, and responsibility a worker's job has, see Bayer and Kuhn, 2018) by a full set of dummy interactions, plus time and industry fixed effects. Data source: *SES* 2018.

size-wage curve (see also Kovalenko, Sauerbier, and Schröpf, 2024, reconfirming our evidence). Finally, and again in line with the cross-sectional data (industry differences across East-West) and our theory, there is a concomitant trend towards smaller plant sizes (at entry). Figure 10 shows that 24% of all employees of an entry cohort used to be at large plants in 1996. This share has declined to 12% by 2013.[30]

Having said this, in 2015, there was a major policy change in Germany that we can expect to affect size-wage curves. Germany, for the first time, introduced a national minimum wage. This was more binding in East Germany (see e.g. Dustmann et al., 2022). While a wage floor does not map one-for-one into $\hat{\omega}$ or otherwise easily into our model, as it would break the log-linear structure, it is clear that it lowers the relative advantage of choosing a small-scale business model with few customers and few low-paid employees. Therefore, we would expect the following predictions: (i) the difference in size-wage curves between East and West Germany should be reduced, (ii) the size of firms at entry should go up in East Germany relative to West Germany, and (iii) productivity convergence between East and West should be accelerated.

[30]These trends are similar when we split the data by East and West Germany.

Figure 11: Changes in convergence, West and East Germany, after minimum wage introduction



Notes: The left panel displays the share of employment of large plants (>249 employees) one year after entry for the periods 2000-2014 and 2015-2018 for East and West Germany. Data source: *AWFP*.
The center and right panels show the log difference in output per hour (center) and compensation per hour (right) between West and East Germany. The blue solid lines are the actual data, the red dashed lines are linear trends estimated on the 2000-2014 data. Data source: *VGR*.

All of these predictions are borne out in the data. First, using *SES* 2018 data, we find that the East-West differences in the size-wage elasticity have become virtually zero (and thus also statistically insignificant), see Table 6.

Second, we use the *AWFP* data (extended to 2018) to compare entry cohorts in terms of the share of employment at large plants before and after the introduction of the national minimum wage. This comparison can be found in the left panel of Figure 11. The East-West difference has shrunk substantially after 2015.

Finally, with all the caveats that come with a simple trend extrapolation exercise, we compare the relative developments of output per hour and compensation per hour in East and West Germany after 2015 to its pre-2015 trend, see the center and right panel of Figure 11. Both in terms of output per hour and compensation per hour, convergence between East and West Germany has substantially accelerated relative to what the pre-minimum wage trend suggests: After 2015, the realized time series are below the predicted trend in every single year. To illustrate the magnitude, the actual compensation and output per hour difference was three log points lower in 2022 than the trend decrease predicted. Given the low pre-minimum wage speed of convergence, this translates into a roughly five-year speed-up of convergence.

6 Conclusion

Large aggregate labor productivity differences persist across regions where government policies (and legal institutions enforcing these) are almost identical. We consider the case of Germany where, more than two decades after reunification, the East German private, non-primary sector remains about 25% less productive than its West German counterpart. We show that this difference in productivity is closely linked to differences in the size distribution of plants, which are, in turn, related to differences in collective bargaining coverage by plant size. In East Germany, collective bargaining is much more concentrated at large plants than it is in West Germany. This selective difference in collective bargaining coverage creates incentives to chose business models in East Germany where the plant and its associated firm stays small. By staying small, the firm avoids paying high collectively-bargained wages, i.e., more size-dependent collective bargaining creates additional labor market monopsony power in East relative to West Germany. Finally, these East-West differences in monopsony power correlate with differences in average wages, productivity, and various measures of business network investments.

We develop a model that merges labor market power and customer acquisition, in the form of business network investments, and show that labor market power distorts the size distribution of firms and lowers, thereby, aggregate labor productivity. When firms face steeper size-wage curves and, thus, have more labor market power, they decide to invest less in business networks because otherwise they would require a larger workforce, which raises wages. This leads to long-run business models relying on smaller production networks for all firms and to a smaller concentration of workers at the most productive firms. Both channels affect aggregate labor productivity adversely. The model, calibrated to the estimated difference in monopsony power and the West German plant size distribution, matches the East German plant size distribution extremely closely and explains about 40 percent of the observed lower labor productivity in East Germany. Put differently, monopsony power in the labor market has strong negative aggregate productivity effects.

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A East-West Differences in Factor Inputs and Labor Market Reallocation

In principle, lower output per worker in East Germany could be the result of differences in the quality and quantity of factor inputs or differences in total factor productivity (TFP). TFP differences, in turn, could result from differences in access to technology or institutions (which is unlikely to be the case in the German context), differences in the capability of the labor market to reallocate workers to firms that become more productive—a sclerotic labor market in East Germany—or a persistent misallocation of workers to relatively unproductive plants (as in our model, where we attribute this misallocation to the disincentives of the most productive plants to build large business networks).

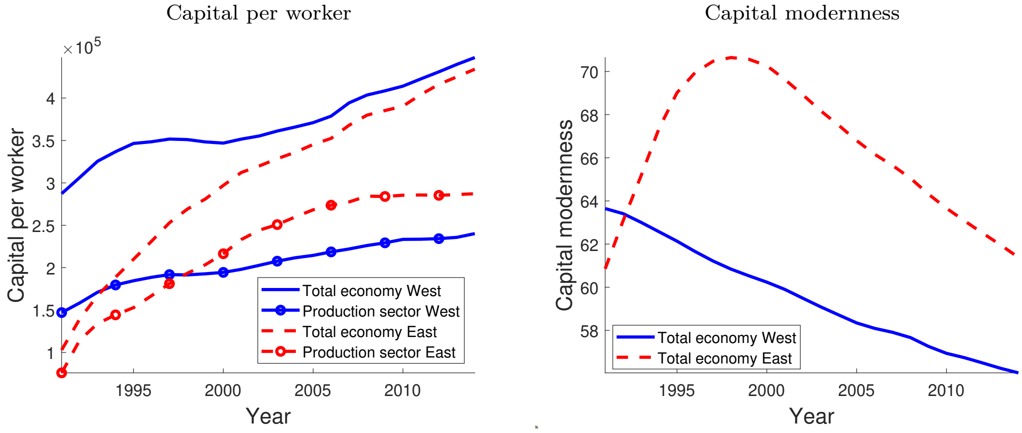
In this appendix, we establish that, first, differences in factor inputs are unlikely the reason behind the observed differences in output per worker. In other words, it has to be TFP.[31] Second, we show that the labor market in East Germany is at least as dynamic as the West German labor market, meaning that labor market sclerosis is not to blame, either.

A.1 Capital and Labor Inputs

Burda (2006) puts forward an explanation for low aggregate labor productivity where capital accumulation is subject to frictions. East Germany had a lower capital stock in 1992, implying low initial labor productivity, and if it takes time for the East to accumulate capital, this would explain a persistent productivity gap. Figure A1 (left panel) compares the (net, i.e., after depreciation) capital stock per worker in East Germany to that in West Germany. It shows that the capital stock per worker was indeed much lower initially, but, differently from output per worker, had almost converged by 2005. In 2014, the difference in the capital stock per worker is only 3%. Thus, with a constant returns to scale Cobb-Douglas aggregate production function and a standard capital share of 30%, this difference in capital intensity would explain 0.9 percentage points of aggregate labor productivity differences.

[31] Mertens and Müller (2022) also argue that the East-West German aggregate output per worker difference in manufacturing can only be explained by TFP differences.

Figure A1: Capital stock



Notes: The left panel displays the net capital stock (after depreciation) per worker in East and West Germany for the total economy and the production sector (manufacturing, mining, utilities, and construction). The right panel displays the modernness of the capital in East and West Germany (net capital divided by gross capital). Data source: *VGR*.

We are particularly interested in differences in the private, non-primary sector. Unfortunately, the German national accounts do not provide the capital stock by detailed industry and region. It does, however, provide data on the production sector (manufacturing, mining, utilities, and construction), and Figure A1 (left panel) shows that, in that sector, East Germany has even overtaken the West German economy in terms of capital intensity by 1998.

In this comparison, capital quality could be a confounding factor if East German plants still produced with outdated capital from before the reunification. Figure A1 in the right panel displays the modernness of capital, i.e., net capital divided by gross capital. Consistent with the large catch-up in capital accumulation shown in the left panel, the capital stock is of a rather young vintage in East Germany suggesting that, if anything, it is of higher quality.

Another potential explanation for the lower aggregate labor productivity in East Germany could be lower quality of labor inputs. If this was the case, then wage differences between East and West Germany should be explainable by measures of worker quality, such as age, sex, education, and occupation. At first inspection, for education and occupation, Table A1 does not suggest that differences in worker quality are a likely explanation. Considering formal education,

Table A1: Worker skills

Education shares					
Low		Medium		High	
West	East	West	East	West	East
11.58	3.66	74.79	83.75	13.63	12.59

Work task shares							
Low		Medium		Semi-high		High	
West	East	West	East	West	East	West	East
40.09	44.31	42.98	41.99	7.68	5.79	9.24	7.91

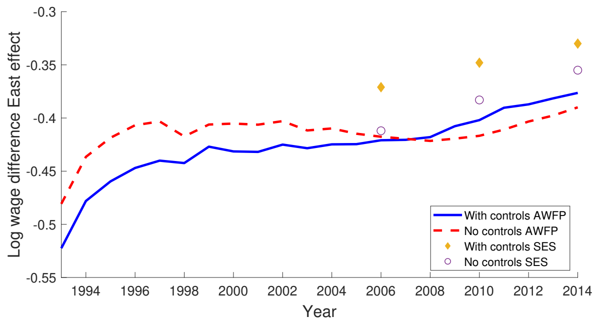
Note: The table displays the shares of education and occupation categories in West and East Germany. Education: Low: Workers without formal vocational training. Medium: Workers with formal vocational training and/or higher education entrance qualification. High: Workers with a university degree. Task: Low: Agricultural occupations, elementary manual occupations, elementary personal services occupations, elementary administrative occupations. Medium: Skilled manual occupations, skilled services occupations, skilled administrative occupations. Semi-high: Technicians, associate professionals. High: Professional occupations, managers. (see Blossfeld, 1987) Data source: *AWFP* 2006–2014.

East Germany tends to have, if anything, a more skilled workforce with fewer workers without formal training. Considering tasks, there is some evidence that workers in West Germany perform tasks that require somewhat more skills but differences are minor. To analyze this more formally, we estimate in the *SES*, at the worker-level, the following regression for the years 2006, 2010, and 2014:

$$\ln w_{it} = \alpha_0 + East_i + F(age_{it}, sex_{it}) + educ_{it} + occ_{it} + \epsilon_{it}, \tag{A.1}$$

where $East_i$ is a dummy variable equal to one if a worker works at a plant that is located in the East, and *age*, *sex*, *educ*, and *occ* are sets of dummy variables for workers' age, sex, education, and occupation, respectively. We estimate two versions of this regression, one with worker observables, age and sex fully interacted, and one without any observables. This restricted regression simply estimates the mean log-wage differences between East and West Germany for each year. The regression with observables does the same but controlling for different worker skill distributions in East and West Germany. Figure A2 compares the two regressions.

Figure A2: Worker quality



Notes: The figure displays the predicted log wage effect of a plant being located in East Germany (*No controls*) and the predicted effect of a plant being located in East Germany when controlling for worker observables (*With controls*). Estimation is based on the non-primary, private sector from either the *SES* or the *AWFP*. Worker observables in the *SES* are age and sex fully interacted, education, and occupation. Worker observables in the *AWFP* are the share of employment of workers across different ages, sex, education, and task categories at the plant level.

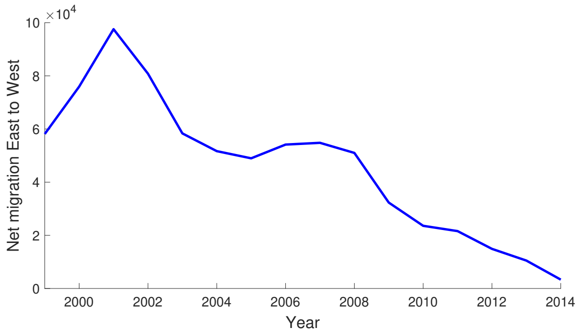
It shows that the mean difference in log wages and the mean difference in log wages after controlling for observable worker characteristics are very similar. Controlling for worker observables explains some of the lower wages in East Germany but, even among observationally identical workers, wages are about 0.35 log points lower in East Germany.

The *AWFP* data allows us to extend this analysis back in time. However, the *AWFP* being a plant-level data set, we can only do so at the plant level, using plant-level average earnings and plant-level shares of worker observables. In addition, the *AWFP* summarizes occupations in four broad groups called work tasks. This leads to the following plant-level regression for each year:

$$\ln w_{jt} = \alpha_0 + East_j + age_{jt} + sex_{jt} + educ_{jt} + task_{jt} + \epsilon_{jt}, \tag{A.2}$$

where $\ln w_{jt}$ is the log average wage at plant j in year t, $East_j$ is a dummy variable equal to one when plant j is located in the East, and age_{jt} is the share of employment of workers across different age categories, sex_{jt} the share of employment of workers across different sex categories, $educ_{jt}$ the share of employment across different education categories, and $task_{jt}$ the share of employment across different task categories at the plant. We demean all covariates by their West German

Figure A3: Net migration



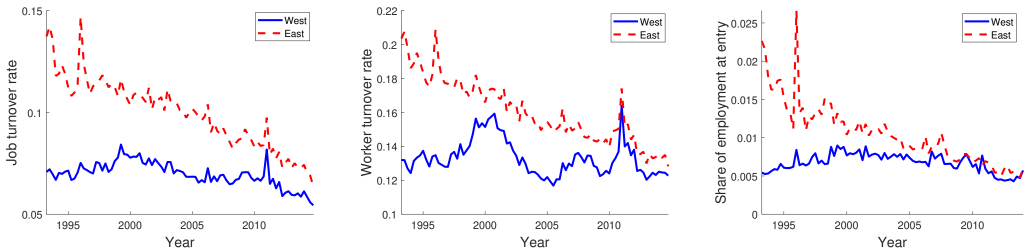
Notes: The figure displays the net migration from East to West Germany. The data is from the Federal Statistical Office of Germany (Bevölkerung und Erwerbstätigkeit Fachserie 1 Reihe 1.2).

mean and estimate again two versions of the regression, one with the covariates of worker observables and one without it.

Again, as Figure A2 shows, worker observables explain little of the wage differences. In fact, during the early years after reunification, worker characteristics have been somewhat better in East relative to West Germany.[32] The relative improvement of the West German worker skill distribution has in part resulted from an outflow of workers from East Germany, see Uhlig (2006). However, as just argued, the overall distributions of qualities remain very similar in the two regions. Moreover, Figure A3 shows that net-outflows from the East to the West have constantly fallen since 2000 and essentially converged to zero by 2013. This means that workforce loss in East Germany as a hindrance to convergence would have lost relevance over time.

In line with the above, Fuchs-Schündeln and Izem (2012) also find that plant or job characteristics, rather than worker characteristics, explain the bulk of wage differences between East and West Germany even when unobserved worker heterogeneity is controlled for.

Figure A4: Job and worker turnover rates



Notes: The first panel displays the job turnover rate (the sum of job creation and job destruction). The second panel displays the worker turnover rate (the sum of accessions and separations). The third panel displays the share of employment at plants entering in a quarter. All three panels: private non-primary sector. Data source: *AWFP*.

A.2 Sclerotic Labor Market Reallocation?

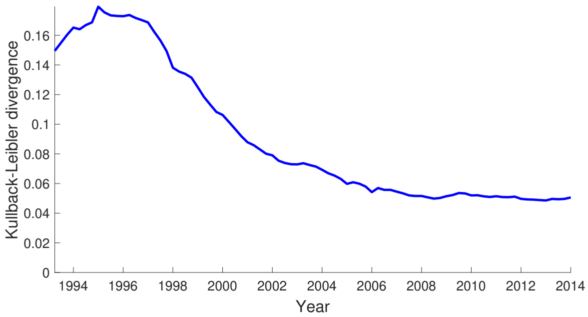
Given that it appears to be neither capital nor the quality of labor that explains productivity differences, the explanation must rest on TFP. In the German context, reunification has been a major shock, and one possibility might be that, even after 30 years, East Germany has failed to reallocate labor from the former state-run, unproductive plants towards more productive plants.[33] Using the *AWFP*, we show, however, that common measures of labor market reallocation are not lower in East Germany.

To this end, we study quarterly job and worker reallocation rates as defined and explained in detail in Bachmann et al. (2021). Figure A4 (a) displays the job turnover rates for East and West Germany. Job reallocation in East Germany has been relatively high following the years after reunification, likely contributing to the rapid productivity growth during these years, yet, missing reallocation does not appear to be the reason for the missing productivity convergence afterward. That is, job reallocation has remained higher in East than in West Germany throughout the sample period. In fact, the amount of job turnover in East Germany was sufficient to destroy and create every job 2.8 times between 1993 and 2015.

[32] We note that a similar quality of the workforce also suggests that East German plants do not remain small because they cannot find high-skilled workers, as in Gomes and Kuehn (2017).

[33] Boeri and Terrell (2002) find that such job reallocation has indeed been important in understanding productivity growth in former Soviet Republic countries. Even for the U.S., the evidence suggests that much of long-run productivity growth is driven by the reallocation of jobs from less to more productive plants (see Foster, Haltiwanger, and Krizan, 2001).

Figure A5: Industry convergence



Notes: The figure displays the Kullback-Leibler divergence index between the West and East German employment distributions over 21 industries from the private non-primary sector: $KL = \sum_{i=1}^{2} 1P(x_i)log\frac{P(x_i)}{Q(x_i)}$, where $P(x_i)$ is the employment share of industry i in West Germany, and $Q(x_i)$ is the corresponding share in East Germany. Data source: *AWFP*.

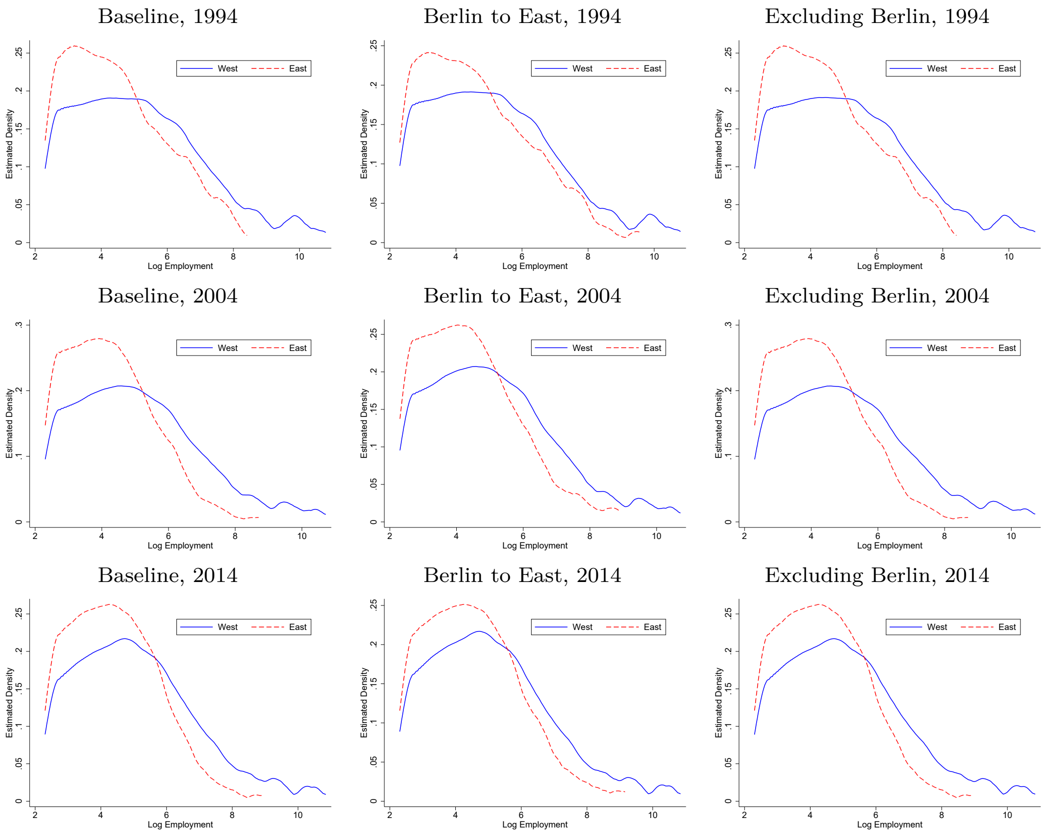
An economy may reallocate workers across plants also without reallocating jobs, for example, to improve match quality between existing jobs and workers. Figure A4 (b) shows that East Germany also does not fall short in terms of worker reallocation relative to the West. In particular, worker reallocation has been particularly high after reunification in East Germany and has nearly converged to the West level afterward. Dauth, Findeisen, Lee, and Porzio (2022) show that the high labor reallocation after the reunification was, indeed, from low- to high-paying plants, contributing to the initial rapid wage growth in East Germany.

The third panel, Figure A4 (c), considers another notion of reallocation, namely, that arising from new plant entry. It displays the share of total employment in a quarter that is due to employment at plant start-ups. Again, if anything, East Germany is the economy with more reallocation.

Yet another notion of reallocation is the growing and shrinking of industries. Since the industry composition has been significantly different in East Germany at the time of reunification, it could be that East Germany failed to reallocate jobs to more promising industries. To better understand the role of different industry structures between the two regions, Figure A5 plots the Kullback-Leibler divergence as a measure of the distance between the West and East German employment distributions over 21 industries. Initially, the industry distributions have been different but this difference has decreased between 1995 and 2008. Neither does the period of high productivity growth in East Germany, that is the years before 1995, coincide with convergence in industry structure, nor does the period of convergence in industry structure, that is 1995 to 2008, exhibit particularly strong aggregate productivity convergence. Most importantly, when looking at productivity differences within industries, as already seen in Figure 4, differences in output per worker are as large within industries as in the economy as a whole: East Germany is less productive in each industry, and differences range from 0.44 log differences in finance to 0.08 in electricity and water supply.

B Further Data on Plant Size Distributions in East and West Germany

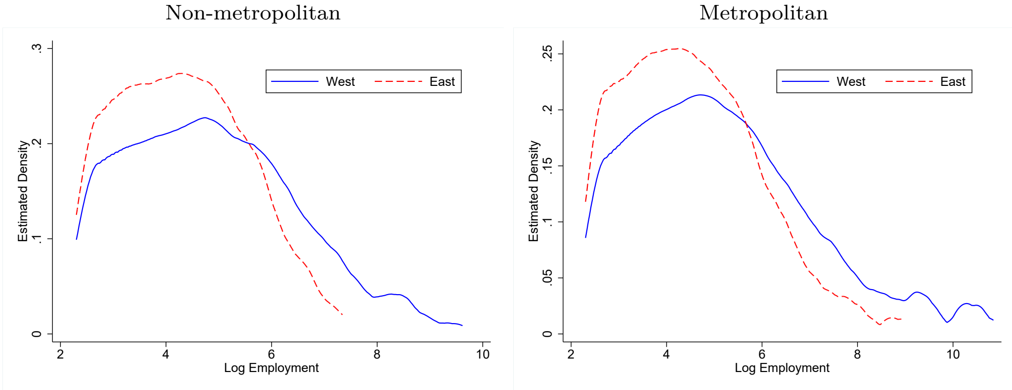
Figure B1: Size distribution *AWFP*



Notes: The figure displays employment-weighted plant size distributions in form of an estimated density function (by a Gaussian kernel smoother) in the total private, non-primary sector. Data source: *AWFP*. The first first column treats Berlin as part of West Germany (our baseline case), the second column treats Berlin as part of East Germany, the last column excludes Berlin.

In this appendix, we show that differences in the plant size distribution extend to earlier time periods and are neither driven by our baseline treatment of Berlin as part of West Germany, nor by differences in urbanization between East and West Germany. To that end, we use the *AWFP* data going back to 1994 and use the information on plants' locations at the German "Kreis" (county) level (which are not available in the *SES*).

Figure B2: Size distribution *AWFP* metropolitan areas, 2014



Notes: The figure displays employment-weighted plant size distributions in form of an estimated density function (by a Gaussian kernel smoother) in the total private, non-primary sector, splitting the sample by plants being located in a non-metropolitan area (left panel) or metropolitan area (right panel). Metropolitan areas are defined as in Dijkstra, Poelman, and Veneri (2019), based on functional urban areas. Data source: *AWFP*.

Figure B1 displays the density of plants over log employment in East and West Germany starting in 1994. The East-West size distribution differences have been fairly stable between 1994 and 2014. What is more, the figure also shows that the finding of missing large plants is robust to the assignment of Berlin to West Germany (first column) as in our baseline (for data availability reasons in the *SES*), to the assignment of Berlin to East Germany (second column), or to the exclusion of Berlin (third column).

Figure B2 displays plant size distributions conditional on a plant being located in a metropolitan area. To define these areas, we use the definition from Dijkstra et al. (2019). The figure shows that metropolitan areas have more employment at large plants than non-metropolitan areas (the estimated employment density in the right panel has a fatter right tail). Importantly, however, even within each area type, the plant size distribution in East Germany is shifted to the left relative to West Germany and displays a less fat right tail.

C Industry Classifications

Table C1: Industry classifications

	SES: WZ2008	*SES:* WZ2003	*MIP:* WZ2008	*VGR:* WZ2008
MFT	10–15	15	10–15	10–15
MWP	16–18/31–32/58–60	20	16–18/31–32/58–60	16–18/31–33/58–60
MCP	19–23	22/25–26	19–23	19–23
MME	24–25/28	30	24–25/28	24–25/28
MLE	26–27	32	26–27	26–27
MVE	29–30	37	29–30	29–30
UTL	35–39	36/43/90	35–39	35–39
CON	41–42	45	–	41–43 (CON)
COP	43	46/47	–	
WHC	45–46	48	46	45–47
RTO	47/33	51	33	
TRA	49–51/61–63	53–54	49–51/61–63	49–53/61–63 (TRA)
STO	52–53	57	52–53	
TUR	55–56	52	–	55–56
BAN	64	63	64	64–66 (FIN)
INS	65–66	64	65–66	
RNS	68/72–75	71	72–74	68/72–75
TES	69–71	72	69–71	69–71
RES	77	77	–	
BAC	78–81	78	78–81	77–82 (OTS)
OTS	82	93	82	

Notes: The table provides a crosswalk that maps the 21 industries used in this paper into the industry classifications used by the *SES*, the 2003 and 2008 industry classifications, the 2008 classification in the *MIP*, and the SNA-ISIC-A38-level industry classification from the national accounts (also based on WZ08). The latter is less detailed, and we have to group some industries. Parentheses show the name we give to the respective industry group. *MFT*: Food and textile manufacturing, *MPW*: Paper and wood manufacturing, *MCP*: Chemical and plastic manufacturing, *MME*: Metal manufacturing, *MEL*: Electronics manufacturing, *MVE*: Vehicle manufacturing, *UTL*: Utilities, *CON*: Construction, *COP*: Construction preparations, *WHC*: Wholesale and car retail, *RTO*: Other retail, *TRA*: Transportation, *STO*: Storage, *TUR*: Tourism, *BAN*: Banking, *INS*: Insurance, *RNS*: Research services, *TES*: Technical services, *RES*: Rental services, *BAC*: Building and area care, *OTS*: Other services.

Industry classifications have undergone several revisions since reunification. The *AWFP* data contains WZ08 2-digit “Abteilungen” as industry classification. Also, the 2010 and 2014 samples of the *SES* use the 2-digit WZ08 classification. The 2006 sample from the *SES* uses the WZ03 classification. The *MIP* data uses the 2-digit WZ08 classification but excludes some industry groups owing to confidentiality concerns. Finally, national accounts are organized by the SNA-ISIC-A38 level of the WZ08 classification. The latter is less fine grained than the 2-digit level. Table C1 provides a cross-walk across these different classifications.

D Robustness of the Size-Wage Nexus

This appendix provides a number of robustness checks to our baseline estimate of the size-wage nexus. We start with worker-plant-level data from the *SES*, followed by analysis with plant-level data from the *AWFP*, followed, in turn, by a worker-firm-level analysis from the *SES*.

D.1 Worker-Level Data (SES)

Table D1: More on the size-wage relationship

	Non-primary private sector	
	Quadratic	Cubic
Difference $\hat{\omega}_E - \hat{\omega}_W$	1.9 (0.3)	2.0 (0.3)
N (in thousands)	2365	2365
	Adding part-time	More region-specific controls
Difference $\hat{\omega}_E - \hat{\omega}_W$	1.8 (0.2)	1.8 (0.3)
N (in thousands)	3074	2365

Note: The table displays the estimated difference in the size-wage relationships for the non-primary private sector in West and East Germany. Standard errors are in parentheses. All coefficients are multiplied by 100 for better readability. *Quadratic*: Controls for a workers' age and sex by a full set of dummy interactions, plus time and industry fixed effects and a region-specific second order polynomial in size. *Cubic*: Controls for a workers' age and sex by a full set of dummy interactions, plus time and industry fixed effects and region-specific 3rd order polynomial in size. The polynomials are constructed such that the displayed coefficient, which is the coefficient on the first-order term, coincides with the sample average first derivative. *Adding part-time*: The same as our baseline estimate but including part-time workers in the sample. *More region-specific controls*: The same as the baseline estimate but allows workers' age and sex as well as industry effects to be region-specific. Data source: *SES* 2006/10/14.

In Section 3.3, we assume that the size-wage relationship is log-linear. It is possible that the true relationship is non-linear and the steeper estimate for the size-wage relationship in East Germany simply captures this non-linearity. For instance, if the plant size relationship was steeper for small plants, the steeper average size-wage relationship in East Germany would simply partially reflect its higher share of small plants. To allow for this possibility, we augment the regression (1) by a region-specific polynomial term, $F(\ln E_{it}, East_i)$, that is constructed such that its expected derivative with respect to $\ln E_{it}$ is zero for both regions. Concretely, we consider a 2nd-order and a 3rd-order polynomial for F:

$$\ln w_{it} = \beta_0 + \beta_E\, East_i + \hat{\omega}_W \ln E_{it} + (\hat{\omega}_E - \hat{\omega}_W)\, East_i \ln E_{it} + \beta x_{it} + F(\ln E_{it}, East_i) + e_{it}. \tag{D.1}$$

The first panel of Table D1 shows that allowing for these higher-order polynomials leads to very similar estimates of the average elasticity difference $\hat{\omega}_E - \hat{\omega}_W$.

Furthermore, recall that we compute the baseline estimate using a sample of full-time workers. The distribution of full-time and part-time workers in East and West Germany is somewhat different, and, hence, it is natural to ask whether our results are robust to including part-time workers. The bottom panel of Table D1 displays estimates of the size-wage relationship in East and West Germany when we include part-time workers. This leads, if anything, to an even steeper size-wage curve in East relative to West Germany. Finally, we allow worker characteristics and industry effects to have heterogeneous effects on wages across the two regions ("More region-specific controls"). To do this, we estimate the size-wage regression, now including additionally East/West-specific two-digit industry fixed effects and East/West-specific effects of worker characteristics (age and sex). That is, we allow in a flexible way for worker sorting based on observables to have different wage effects in the two regions and industry-level demand to be different across the regions. Again, we find that the differences in the size-wage elasticities become even a little larger than in our baseline specification.

D.2 Plant-Level Data (*AWFP*)

In Section 3.3, we control for worker heterogeneity and worker sorting by observable worker characteristics: age, sex, education, occupation, and job levels. The plant-level *AWFP* data together with Bellmann, Lochner, Seth, and Wolter (2020) allows us to control for unobserved worker heterogeneity, too. Specifically, Bellmann et al. (2020) estimate the following regression for all German plants for three time periods (1998-2004, 2003-2010, and 2010-2014) using the matched employer-employee data from the German social security records:

$$\ln w_{ijt} = \alpha_0 + \alpha x_{it} + \phi_j + \gamma_i + \epsilon_{ijt}, \tag{D.2}$$

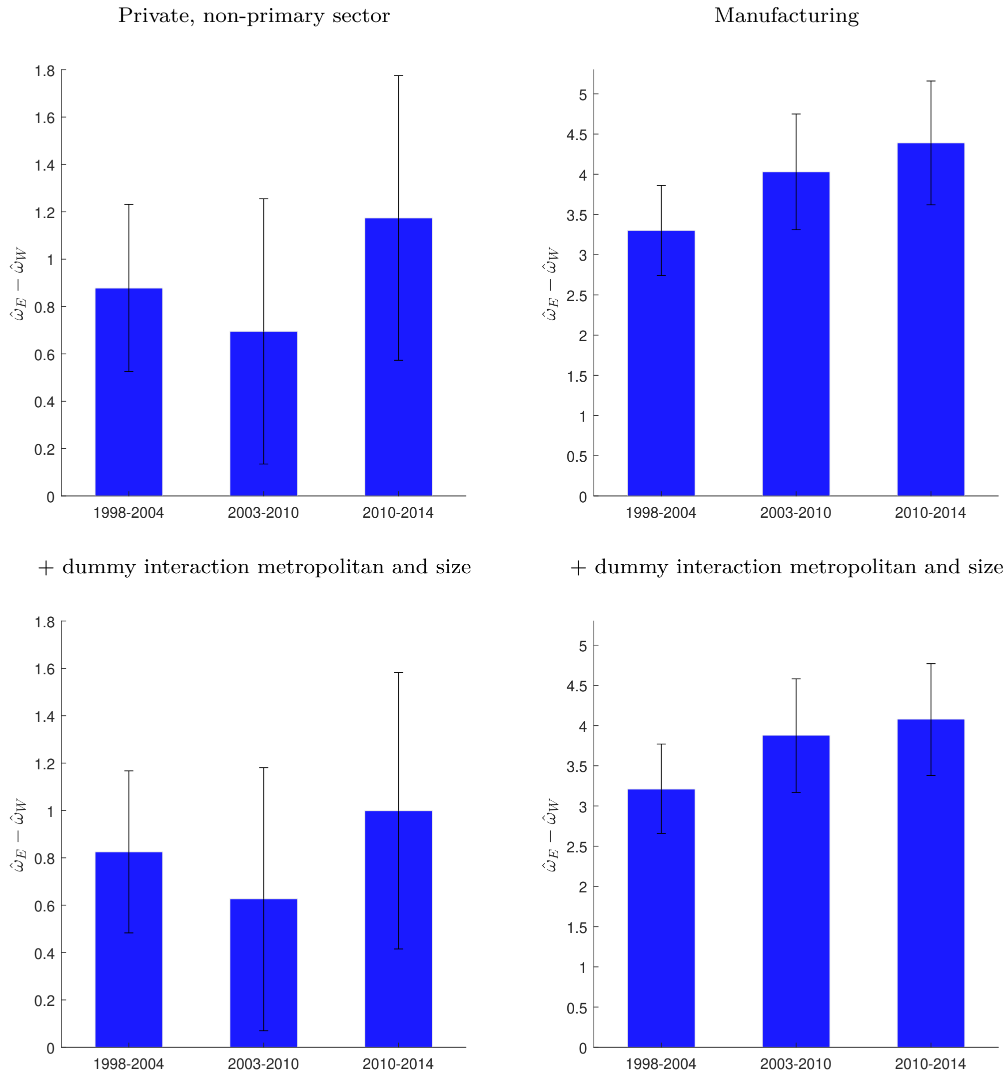
where w_{ijt} are the daily earnings of worker i at plant j in period t, x_{it} are time-varying worker characteristics, γ_i is a worker fixed effect, and ϕ_j is a plant fixed effect. They provide an estimate of the plant fixed effect, $\hat{\phi}_j$, which we match to the *AWFP* data. This plant fixed effect equals the average wage of a plant controlling for its worker characteristics (observed and unobserved). We then can use this average wage in our size-wage regression. That is, we estimate the following regression:

$$\hat{\phi}_j = \beta_0 + \beta_E \, East_j + \hat{\omega}_W \ln E_j + (\hat{\omega}_E - \hat{\omega}_W) \, East_j \ln E_j + \beta x_j + e_j, \tag{D.3}$$

where x_j are controls that include industry fixed effects in the baseline case and a dummy size interaction for non-metropolitan areas in an extension.

The left panel of Figure D1 plots the estimates for $\hat{\omega}_E - \hat{\omega}_W$ for the private, non primary sector for all three sample periods (top row: baseline, bottom row: controlling for non-metropolitan areas). Again, we find that East Germany faces a relatively steeper size-wage, more precisely size-daily-earnings, relationship. The right panel repeats the analysis but restricts it to the manufacturing sector. Reassuringly and as in our baseline results, size-wage differences are particularly pronounced in manufacturing. In other words, these regressions suggests that our baseline findings are not driven by sorting on unobservables. We note that the estimated East-West elasticity difference for the private, non-primary sector is somewhat smaller compared to our baseline (an elasticity of one vs 1.6 percent). This baseline uses practically uncensored hourly wages. The alternative interprets daily top-coded earnings as wage data. This means that deviations from full time hours lead to measurement error in wages in the *AWFP* data. This measurement error can be expected to vary systematically with plant size stemming from the larger flexibility of work hours at larger plants. This effect is likely to be less important in the manufacturing sector, where we find very similar elasticities across the two approaches: workers in that sector are more likely to work full time. The bottom row of the figure shows that differences in the steepness of the size-wage curves are also unlikely to be driven by the fact that East Germany is less metropolitan.

Figure D1: Plant-level size-wage differences



Notes: The figure displays the difference in the size-wage, more precisely the size-daily-earnings, relationship between East and West Germany when the size-wage relationship is estimated using plant-level data as in (D.3). It plots the OLS estimate of $(\hat{\omega}_E - \hat{\omega}_W)$. Error bands are estimated using asymptotic heteroskedastic robust standard errors. The plant-level fixed effects are provided by the *IAB*. The bottom panel repeats the top panel regressions augmented by a dummy for metropolitan area plus an interaction of this dummy with size. Metropolitan areas are defined as in Dijkstra et al. (2019), based on functional urban areas. Data source: *AWFP*.

Moreover, one can ask whether our result of a steeper size-wage curve is driven by high-skill workers in East Germany sorting more into larger plants. Lochner, Seth, and Wolter (2020) (c.f. their Table B.4) shows that this is not the case. If anything, high-skilled workers sort more into large plants in West Germany which is consistent with our observation in Section 3.3 that the difference in the steepness of the size-wage curve becomes more pronounced the more we control for additional worker observables.

D.3 Firms (SES 2006)

The following Table D2 shows that the size-wage nexus is also steeper in East than in West Germany, when we base the estimation on firm size instead of plant size. Specifically, we assign a wage contract now to the firm to which the plant associated with the wage contract belongs. Only the *SES* 2006 data contains the total number of workers of the plant-owning firm. We find a 2.2 percentage point higher elasticity in East Germany compared to West Germany in the baseline specification, see Table D2, which is even higher than our baseline estimate of 1.6 percentage points. We conclude that, as with the plant size data, the missing large firms are likely due to steeper size-wage curves in East Germany.

Table D2: Size-wage elasticities: Firms

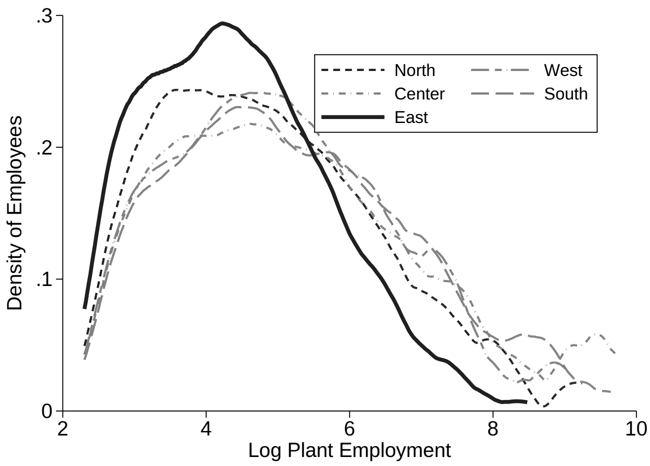
	Non-primary private sector		
	Baseline	Occupation × Education	Job level × Education
Size-Wage elasticity, West, $\hat{\omega}_W$	5.7 (0.2)	4.6 (0.1)	4.2 (0.2)
Difference in elasticities, $\hat{\omega}_E - \hat{\omega}_W$	2.2 (0.4)	2.3 (0.3)	2.7 (0.3)
Implied elasticity, East, $\hat{\omega}_E$	7.9	6.9	6.9
N (in thousands)	1096	1096	1030

Notes: The table displays the estimated size-wage elasticities for the non-primary private sector in West and East Germany in 2006, using the size of the firm that owns the plant, where a worker works. Standard errors are in parentheses. All coefficients are multiplied by 100 for better readability. *Baseline*: Controls for a workers' age and sex by a full set of dummy interactions, plus time, and industry fixed effects. *Occupation × Education*: Controls for a workers' age, sex, education, and occupation by a full set of dummy interactions, plus time and industry fixed effects. *Job level × Education*: Controls for a workers' age, sex, education, and job level (five levels, coding the level of autonomy, complexity, and responsibility a worker's job has, see Bayer and Kuhn, 2018) by a full set of dummy interactions, plus time and industry fixed effects. Data source: *SES* 2006.

E More Robustness

E.1 Analysis with a Finer Regional Resolution for West Germany

Figure E1: Plant-size distributions



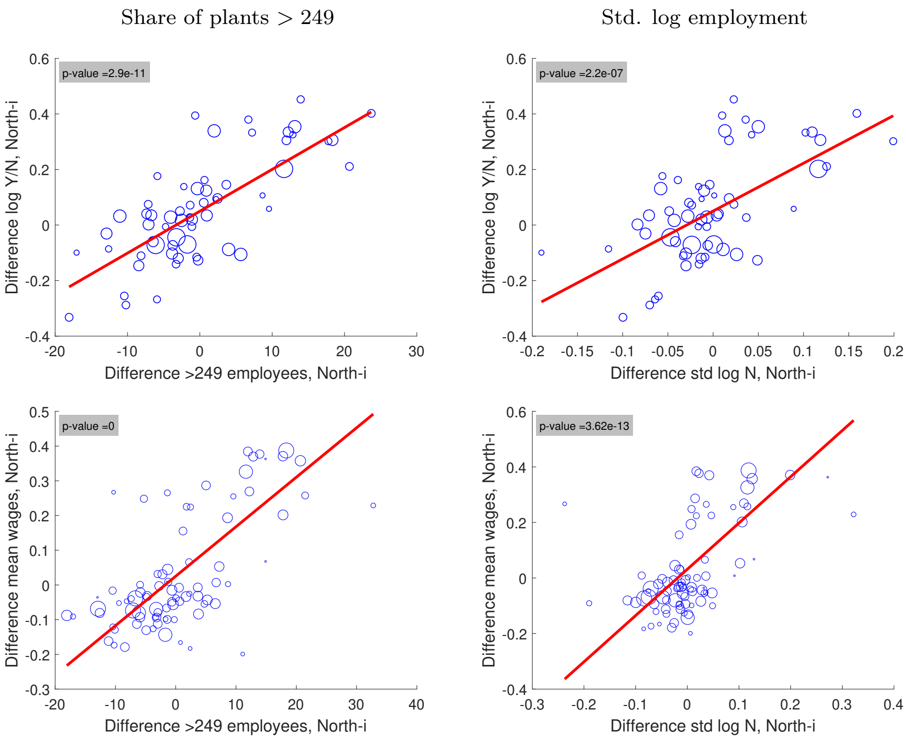
Notes: The figure displays the employment-weighted plant size distributions for five German regions, subdividing West Germany in four regions. It displays an estimated density function (by a Gaussian kernel smoother) in the total private, non-primary sector. Data source: *SES* 2006/10/14.

Our baseline analysis distinguishes only between East and West Germany. The *SES* data allow us to further split up West Germany in four regions: North, West, Center, and South.[34] This appendix extends the analysis and exploits the additional variation coming from the four regions which make up West Germany. We find the same qualitative patterns as in the main text, however, the relationships have a higher statistical significance.

Figure E1 displays the plant size distributions for all five regions. It first shows a visible distinction between East German and all West German plant size distributions. East Germany has, by far, the most missing large plants. Second, there is variation among the West German regions, which we exploit in the following.

[34]North: Schleswig Holstein, Hamburg, Bremen, Berlin, and Lower Saxony; West: Northrhine-Westphalia; Center: Hesse, Rhineland Palatinate, and Saarland; South: Baden-Württemberg and Bavaria. East remains: Thuringia, Saxony, Saxony-Anhalt, Mecklenburg Western Pomerania, and Brandenburg.

Figure E2: Productivity and wage differences and large plants by industry



Notes: Each dot represents an industry/region combination and displays the difference to the same industry in the North region in Germany. The top panels relate 2014 log differences in output per worker to the share of employment at plants with more than 249 employees (left) and the standard deviation of log plant employment (right). Output is measured as gross value added, which is the GDP concept available at the regional level, because product-specific subsidies and taxes (the difference between the two) are only available at the national level. The lines show (VGR) employment-weighted least squares regressions. The bottom panels relate differences in mean log wages to the same plant size measures. The lines show (*SES*) employment-weighted least squares regressions. Data sources: *SES* 2006/10/14 (plant sizes, wages) and *VGR* (labor productivity).

Figure E2 is the analog to Figure 4 in the main text. Those industry/region combinations that have particularly few large plants operating also have low output per worker and low average wages. Table E1 shows that these relationships are statistically significant at the 1% level.

Next, we produce with Figure E3 the analog to Figure 5 in the main text. That is, we use data for 21 industries paired with the five regions to revisit the relationship between steeper size-wage curves and missing large plants and low wages. The figure displays in the two top panels for each industry within each

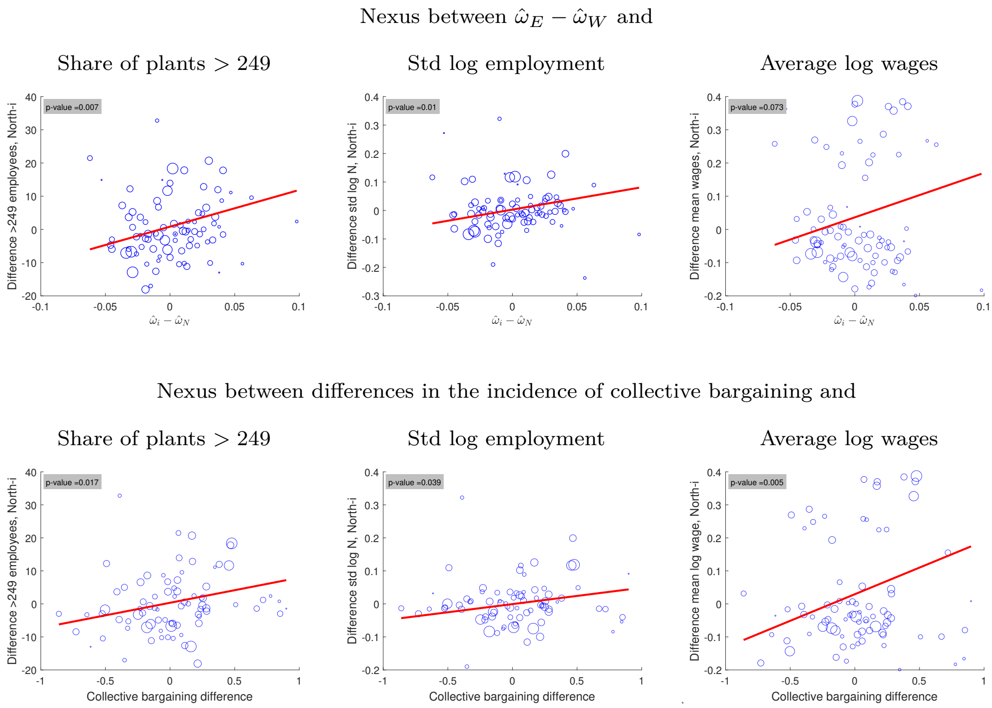
Table E1: P-values

	East-West	East-West + finance dummy
Y/N, > 249	0.044	0.091
Y/N, Std log	0.097	0.149
Wages, > 249	0.009	0.001
Wages, Std log	0.020	0.009
> 249, $\hat{\omega}_E - \hat{\omega}_W$	0.185	0.021
Std log, $\hat{\omega}_E - \hat{\omega}_W$	0.142	0.030
Wages, $\hat{\omega}_E - \hat{\omega}_W$	0.015	0.031
> 249, Collective	0.132	0.075
Std log, Collective	0.035	0.023
Wages, Collective	0.044	0.060
	Finer West regions	Finer West regions + finance dummy
Y/N, > 249	0.000	0.000
Y/N, Std log	0.000	0.000
Wages, > 249	0.000	0.000
Wages, Std log	0.000	0.000
> 249, $\hat{\omega}_E - \hat{\omega}_W$	0.007	0.005
Std log, $\hat{\omega}_E - \hat{\omega}_W$	0.011	0.006
Wages, $\hat{\omega}_E - \hat{\omega}_W$	0.073	0.072
> 249, Collective	0.017	0.016
Std log, Collective	0.039	0.033
Wages, Collective	0.005	0.005

Notes: The table displays p-values (two-sided tests) from the regression lines in Figures 4, 5, E2, and E3. The last column repeats the regressions from the second column adding a dummy for the financial sector, taking into account that this sector is particular in terms of its branching structure and, therefore, in terms of its definition of a plant as a production unit. Data sources: *SES* 2006/10/14 and *VGR*.

region the difference in the size-wage nexus against the difference in the share of employment at large plants (left panel), the difference in the standard deviation of log employment (center panel), and the difference in mean log wages (right panel). Those industry/region combinations that have particularly steep size-wage curves also have relatively few large plants operating and have low wages in that industry/region. Table E1 shows that these relationships are again statistically significant.

Figure E3: The share of large plants, wages, the size-wage nexus, and collective bargaining



Note: Each dot represents an industry/region combination and displays the difference to the same industry in the North region in Germany. The top panel relates differences in the share of employment at large plants, the standard deviation of log plant employment, and average log wages to differences in size-wage relationships. The bottom panel relates differences in the share of employment at large plants, the standard deviation of log plant employment, and average log wages to the following double difference: $[\log P(C|L, R_i) - \log P(C|S, R_1)] - [\log P(C|L, R_i) - \log P(C|S, R_1)]$, where $P(C|\cdot)$ is the conditional probability of a worker being subject to collective bargaining in our sample in (L)arge (>249 employees) or (S)mall ($\leq$ 249 employees) plants in region 1 (North) and region i. The lines show weighted least square regressions. Data source: *SES* 2006/10/14.

The bottom panels of Figure E3 show on the x-axes, for each industry, the double difference in the incidence of collectively bargained wage contracts between large and small plants and between regions. We again plot this double difference against our two measures of differences in the plant size distribution: the share of employment at large plants (left panel) and the standard deviation of log plant-level employment (center panel). Moreover, the right panel shows the relationship with industry/region differences in average log wages. The relationship between collective bargaining incidence differences and plant size differences is positive. Industry-region combinations in which the incidence of collectively bargained wages increases relatively more in plant size are those industry-region combinations where large plants are particularly missing. Similarly, the relationship between collective bargaining incidence differences and differences in average log wages is positive. Industry-region combinations in which the incidence of collectively bargained wages increases relatively more in plant size are those industry-region combinations where plants pay lower average wages. Table E1 shows that these relationships are statistically significant.

E.2 Robustness on Customer Networks and the Size-Wage Nexus

Figure 7 in the main text does not control for other industry-level differences. Table E2 repeats the exercise controlling for industry averages in product and industry characteristics, i.e. innovation intensity, replaceability of products, openness to trade and novelty of products. The results are unchanged.

Table E2: Industry-level regressions

	Marketing expenditures to sales (in %)			Investment in new distribution channels (in %)		
$\hat{\omega}_E - \hat{\omega}_W$	28.5	37.6	32.8	2.3	2.3	1.8
	(6.1)	(8.6)	(9.9)	(0.7)	(0.9)	(1.1)
N	87	52	52	52	52	52
	Customer diversity (in %)			Supplier diversity (in %)		
$\hat{\omega}_E - \hat{\omega}_W$	187.7	229.7	218.2	145.7	123.9	141.2
	(61.1)	(62.3)	(65.2)	(64.5)	(60.4)	(58.0)
N	17	17	17	17	17	17
Time FE (top panel)	Y	Y	Y	Y	Y	Y
Baseline controls	N	Y	Y	N	Y	Y
Additional controls	N	N	Y	N	N	Y

Notes: The table displays the coefficient on the estimated size-wage elasticity difference by industry (naturally scaled) in industry-level linear regressions for: (top-left) expenditures on marketing, relative to sales; (top-right) whether a firm reports to have invested in new distribution channels; (bottom-left) the share of sales that do not go to the three most important customers (in terms of sales); and (bottom-right) the share of purchases that do not come from the three most important suppliers (in terms of purchases). Data comes from the Mannheim Innovation Panel and are aggregated up to the industry year level, sales-weighted. The top panel uses the biannual data from 2006-2014, the bottom panel only from 2010. Samples based on availability of the corresponding questions. All regressions are weighted by industry size. All top panel regressions control for a time fixed effect. Baseline controls include industry differences in innovation intensity, and how simple it is to be replaced by a competitor. Additional controls include industry differences in exporting intensity and the share of new products in sales.

F Details on the Model

Here we provide further details for model derivations left out in the main text.

F.1 Cost Minimization by Bundlers

Let Y_j denote the final consumption good produced by bundler j using a Dixit-Stiglitz aggregator:

$$Y_j = \left(\int \gamma_i \theta_{ij} y_{ij}^{\frac{\eta-1}{\eta}} \, di \right)^{\frac{\eta}{\eta-1}}, \tag{F.1}$$

where y_{ij}, is the input from the intermediate good producer i (the total mass of all intermediate producers being one), the indicator $\gamma_i = 1$ if the producer has entered the market, and $\theta_{ij} = 1$ if the producer forms a business relationship with bundler j. This implies that the demand for producer i's product by bundler j is given by

$$y_{ij} = \gamma_i^\eta \theta_{ij}^\eta \left(\frac{p_{ij}}{\bar{P}_j} \right)^{-\eta} Y_j = \begin{cases} \left(\frac{p_{ij}}{\bar{P}_j} \right)^{-\eta} Y_j & \text{if } \gamma_i = \theta_{ij} = 1, \\ 0 & \text{otherwise,} \end{cases} \tag{F.2}$$

where $\bar{P}_j$ is the cost minimizing price at which bundler j sells its bundle, and p_{ij} is the price of the intermediate good charged by producer i to bundler j.

The cost-minimizing price of bundler j, the ideal price index, is given by

$$\bar{P}_j = \left(\int (\gamma_i \theta_{ij})^\eta p_{ij}^{1-\eta} di \right)^{\frac{1}{1-\eta}}, \tag{F.3}$$

which can be written as

$$\bar{P}_j = \left(\int (\gamma_i \theta_{ij})^\eta di \right)^{\frac{1}{1-\eta}} \left(\int p_{ij}^{1-\eta} di \right)^{\frac{1}{1-\eta}} \tag{F.4}$$

because we assume that prices and γ and θ are independent. The latter reflects random matching between intermediate good producers and bundlers, the former is tantamount to assuming, without loss of generality, that inactive producers set a price as if they were active and could sell (a weakly dominant strategy). What is more, random matching implies that the integral $\left[\int (\gamma_i \theta_{ij})^\eta di \right]^{\frac{1}{1-\eta}}$ does not depend on the specific bundler j which leads to Equation (3) in Section 4.1:

$$\bar{P}_j = (\Gamma\bar{\Theta})^{\frac{1}{1-\eta}}\hat{P}_j \tag{F.5}$$

$$\hat{P}_j = \left(\int p_{ij}^{1-\eta}di\right)^{\frac{1}{1-\eta}} \tag{F.6}$$

where Γ is the mass of all active producers, $\bar{\Theta}$ is the average fraction of active producers connected with a bundler, which by symmetry is also the average fraction of bundlers that an active producer sells to (and therefore has no j index), and $\hat{P}_j$ is the average price charged by intermediate good producers.

F.2 Optimal Business Network Investments

The intermediate good producer maximizes gross profits net of investments in the business network but takes into account that wages are a function of the total number of employees. To connect to one additional bundler, the intermediate good producer has to invest $\mu\bar{P}$ (μ measures costs in terms of the output good). The resulting operating profits are:

$$\Pi_i(\Theta_i) = \pi(\Theta_i, w_i(\Theta_i)) - \mu\bar{P}\Theta_i, \tag{F.7}$$

$$w_i(\Theta_i) = \left(\frac{l_i\Theta_i}{\bar{l}\bar{\Theta}}\right)^{\hat{\omega}}. \tag{F.8}$$

To obtain an expression for $w_i(\Theta_i)$, we plug the number of workers, $l_i = \frac{y_i}{z_i}$, required to fulfill the demand from each individual bundler, (F.2), into the size-wage trade-off, (F.8):

$$w_i = \left(\frac{\left(\frac{p_i}{\bar{P}}\right)^{-\eta}\frac{Y}{z_i}\Theta_i}{\bar{l}\bar{\Theta}}\right)^{\hat{\omega}}. \tag{F.9}$$

Next, substituting p_i with the optimal pricing decision, solving for the wage w_i, and summarizing terms, we obtain wages as a function of the mass of bundlers in firm i's network, which is Equation (8) in Section 4.2.3:

$$w_i = z_i^{\frac{(\eta-1)\hat{\omega}}{1+\eta\hat{\omega}}} \bar{w} \left(\frac{\Theta_i}{\bar{\Theta}}\right)^{\frac{\hat{\omega}}{1+\eta\hat{\omega}}}, \tag{F.10}$$

where $\bar{w} = \left[\left(\bar{P}\frac{\eta-1}{\eta}\right)^{\eta} \frac{Y}{l}\right]^{\frac{\hat{\omega}}{1+\eta\hat{\omega}}}$ summarizes the aggregate terms that affect wages. Substituting into operating profits, (F.7), and using (5) yields

$$\Pi_i = \Theta_i \left(\frac{\Theta_i}{\bar{\Theta}}\right)^{\frac{\hat{\omega}}{1+\eta\hat{\omega}}(1-\eta)} z_i^{-(1-\eta)\frac{\hat{\omega}+1}{1+\eta\hat{\omega}}} \bar{P}^{\eta} Y \frac{(\eta-1)^{\eta-1}}{\eta^{\eta}} \bar{w}^{1-\eta} - \mu \bar{P} \Theta_i. \tag{F.11}$$

The optimal Θ_i of a producer follows from the first order condition, $\frac{\partial \Pi_i}{\partial \Theta_i} = 0$, ignoring, for simplicity, that $\Theta_i \leq 1$:

$$\frac{1+\hat{\omega}}{1+\eta\hat{\omega}} \frac{Y}{\mu} \frac{1}{\eta} \left(\frac{\bar{P}}{\bar{w}} \frac{\eta-1}{\eta}\right)^{\eta-1} \left(\frac{\Theta_i}{\bar{\Theta}}\right)^{\frac{\hat{\omega}}{1+\eta\hat{\omega}}(1-\eta)} = z_i^{(1-\eta)\frac{1+\hat{\omega}}{1+\eta\hat{\omega}}}, \tag{F.12}$$

which, solving for Θ_i, simplifies to Equation (9):

$$\frac{\Theta_i}{\bar{\Theta}} = z_i^{\frac{1+\hat{\omega}}{\hat{\omega}}} \left[\frac{1+\hat{\omega}}{1+\eta\hat{\omega}} \frac{Y}{\mu} \frac{1}{\eta} \left(\frac{\bar{P}}{\bar{w}} \frac{\eta-1}{\eta}\right)^{\eta-1}\right]^{\frac{1+\eta\hat{\omega}}{\hat{\omega}(\eta-1)}}. \tag{F.13}$$

Section 4.2.3 argues that an alternative way to express the optimal network choice is in form of a mark-down equation:

$$\frac{w_i}{\bar{P}} = \left[\frac{1+\hat{\omega}}{1+\eta\hat{\omega}} \frac{Y}{\mu} \frac{1}{\eta}\right]^{\frac{1}{\eta-1}} \frac{\eta-1}{\eta} z_i. \tag{F.14}$$

The equation highlights that marginal costs are constant across producers which implies, using the optimal price setting in Equation (4), that all producers charge the same price and sell the same quantity to each bundler they are connected to. In turn, we obtain for the price, using (F.5),

$$\frac{p_i}{\bar{P}} = \frac{\hat{P}}{\bar{P}} = (\Gamma\bar{\Theta})^{\frac{1}{\eta-1}}, \tag{F.15}$$

and, plugging in (4), the real wage is given by:

$$\frac{w_i}{\bar{P}} = \frac{\eta - 1}{\eta} (\Gamma \bar{\Theta})^{\frac{1}{\eta-1}} z_i. \tag{F.16}$$

Comparing (F.16) to (F.14), we obtain Equation (11):

$$\bar{\Theta} = \frac{Y/\Gamma}{\mu} \frac{1}{\eta} \frac{1+\hat{\omega}}{1+\eta\hat{\omega}}. \tag{F.17}$$

F.3 Optimal Firm Size

We want to derive an expression for total employment of a firm $l_i \Theta_i$ as a function of productivity z_i. We do this in three steps. First, we derive an expression for employment per bundler l_i as a function of z_i. Second, we derive an expression for the mass of bundlers, Θ_i, connected to firm i as a function of z_i and, finally, we combine them.

First, using Equation (F.2) together with (F.15), we can show that the optimal quantity sold to a single bundler is the same across firms:

$$l_i z_i = y_i = \left(\frac{p_i}{\bar{P}}\right)^{-\eta} Y = Y (\Gamma \bar{\Theta})^{\frac{\eta}{1-\eta}}. \tag{F.18}$$

Second, taking expectations over (F.13) and using that z_i is assumed to be observed after entry:

$$\left[\frac{1+\hat{\omega}}{1+\eta\hat{\omega}} \frac{Y}{\mu} \frac{1}{\eta} \left(\frac{\bar{P}}{\bar{w}} \frac{\eta-1}{\eta}\right)^{\eta-1}\right]^{-\frac{1+\eta\hat{\omega}}{\hat{\omega}(\eta-1)}} = \mathbb{E}\left(z_i^{\frac{1+\hat{\omega}}{\hat{\omega}}}\right), \tag{F.19}$$

because $\bar{\Theta}$ is the expected value of Θ_i. This implies that we can rewrite (F.13) in the following compact form

$$\frac{\Theta_i}{\bar{\Theta}} = \frac{z_i^{\frac{1+\hat{\omega}}{\hat{\omega}}}}{\mathbb{E}\left(z_i^{\frac{1+\hat{\omega}}{\hat{\omega}}}\right)}. \tag{F.20}$$

Finally, combining (F.18) and (F.20), yields:

$$l_i \Theta_i = z_i^{1/\hat{\omega}} Y (\Gamma \bar{\Theta})^{\frac{\eta}{1-\eta}} \bar{\Theta} \mathbb{E}\left(z_i^{\frac{1+\hat{\omega}}{\hat{\omega}}}\right)^{-1}. \tag{F.21}$$

To calculate the expectations in the above equations, we assume that idiosyncratic productivity, z_i, is log-normally distributed, $z_i \sim LN(\ln \bar{z}, \Sigma^2)$. For any log-normally distributed random variable $z \sim LN(\ln \bar{z}, \Sigma^2)$ and real number x, it holds that:

$$E(z^x) = \bar{z}^x \phi^{x^2}, \quad \text{with} \quad \phi = \exp(0.5\Sigma^2). \tag{F.22}$$

This gives Equations (12) and (13) in the main text:

$$\frac{\Theta_i}{\bar{\Theta}} = \left(\frac{z_i}{\bar{z}\phi} \phi^{-\frac{1}{\hat{\omega}}} \right)^{\frac{1+\hat{\omega}}{\hat{\omega}}}. \tag{F.23}$$

$$l_i \Theta_i = z_i^{1/\hat{\omega}} Y (\Gamma \bar{\Theta})^{\frac{\eta}{1-\eta}} \bar{\Theta} \left(\frac{1}{\bar{z}\phi} \phi^{-\frac{1}{\hat{\omega}}} \right)^{\frac{1+\hat{\omega}}{\hat{\omega}}}. \tag{F.24}$$

G A Simple Model of Monopsony Power

This appendix elucidates the additional output effects arising from the combined presence of customer acquisition, love-of-variety in production, and endogenous producer entry over and above those present in a simple model of monopsony power in the labor market. For this purpose, consider a simplified version of our model in Section 4 without love-of-variety in production, no customer acquisition, and no endogenous producer entry. Producers hire labor, l_i, and combine it with their idiosyncratic productivity, z_i, to produce a homogeneous output good, y_i. We assume again that a producer's wage, relative to the average wage, is log-linear in its size, l_i:

$$w_i = \left(\frac{l_i}{\bar{l}}\right)^{\hat{\omega}} W, \tag{G.1}$$

where again we normalize the wage at the average plant size, W, to unity, making labor the numeraire. Hence, producers' profits are given by their revenues minus labor costs:

$$\Pi_i = P z_i l_i - l_i \left(\frac{l_i}{\bar{l}}\right)^{\hat{\omega}}. \tag{G.2}$$

Taking the first-order condition with respect to labor and rearranging gives a producer's optimal size as a function of its idiosyncratic productivity:

$$l_i = \bar{l} z_i^{\frac{1}{\hat{\omega}}} \left(\frac{P}{1+\omega}\right)^{\frac{1}{\hat{\omega}}}. \tag{G.3}$$

Labor market clearing implies that total labor demand equals the aggregate labor supply of one (just as in our baseline model). Hence, integrating (G.3), where we again assume that z_i is log-normally distributed, yields

$$\int l_i di = \bar{l} \bar{z}^{\frac{1}{\hat{\omega}}} \phi^{\frac{1}{\hat{\omega}^2}} \left(\frac{P}{1+\omega}\right)^{\frac{1}{\hat{\omega}}} = 1. \tag{G.4}$$

Dividing (G.3) by (G.4) to eliminate P and rearranging yields:

$$l_i = z_i^{\frac{1}{\hat{\omega}}} \bar{z}^{-\frac{1}{\hat{\omega}}} \phi^{-\frac{1}{\hat{\omega}^2}}. \tag{G.5}$$

It follows that the output of each producer is:

$$y_i = z_i l_i = z_i^{\frac{1+\hat{\omega}}{\hat{\omega}}} \bar{z}^{-\frac{1}{\hat{\omega}}} \phi^{-\frac{1}{\hat{\omega}^2}}. \tag{G.6}$$

Finally, integrating and normalizing average productivity, $\bar{z}\phi$, to one as in the main text, gives total output as:

$$Y = \int y_i di = \phi^{\frac{2}{\hat{\omega}}}, \tag{G.7}$$

which is the analog to (19):

$$Y = \left(\frac{1}{\mu\eta}\frac{1+\hat{\omega}}{1+\eta\hat{\omega}}\right)^{\frac{1}{\eta-2}} \left(\phi^{\frac{2}{\hat{\omega}}}\right)^{\frac{1}{\eta-2}} \phi^{\frac{2}{\hat{\omega}}},$$

which determines output in our main model. Comparing the two equations highlights the importance of business network investment in our baseline model. The pure monopsony model with heterogeneous producers does, however, feature the labor allocation effect, $\phi^{\frac{2}{\hat{\omega}}}$. This effect is also present in the oligopsonistic model of Berger et al. (2022), see their productivity term $\tilde{Z}$ in Proposition 1.2, which becomes our term after assuming a single market and monopsonistic instead of oligopsonisitic competition. Furthermore, as a corollary, in this simplified model there is no output loss from monopsony power in the labor market when producers are homogeneous, $\phi = 1$, and aggregate labor supply is fixed.

H A Wage Subsidy

The standard output loss associated with monopsony power is underemployment. Given our assumption of fixed aggregate labor supply, this is absent in our model. Instead, Section 4 identifies two additional sources of output loss from monopsony power in the labor market: Allocation of workers away from the most productive producers and underinvestment in business networks. This appendix shows that the standard policy tool to overcome the problem of underemployment, a (proportional) wage subsidy, fails to address these two additional sources of output loss. The intuition for this result, before laying out the argument formally, is as follows: With constant elasticity in goods demand, all producers charge the same markup, and, thus, all prices (relative to wages) move down proportionally with the subsidy. This leaves the share of an individual producer in the total output of a bundler unchanged *if the individual producer's wage does not change relative to other producers*. This also means that individual employment per connected bundler is constant relative to total employment. With isoelastic producer-specific labor supply, it also turns out that the individual share of connected bundlers relative to the average is constant. In the end, all incentives to acquire customers change proportionally with the subsidy. Altogether, this means that the individual share in total employment remains unchanged, and hence, because this share is the only determinant of an individual producer's relative wage, these relative wages indeed remain unchanged, confirming the conjecture above. This leaves entry as the only potential margin to be affected by the subsidy. The subsidy increases, ceteris paribus, the profits of active producers and should, thus, spur entry. However, with fixed aggregate labor supply, average wages adjust one-for-one with the subsidy, eliminating the extra entry incentive as well as any aggregate incentive to acquire more customers.

The formal exposition of this argument follows closely the model of Section 4 and, thus, we will be brief here. Producers receive a proportional wage subsidy, τ_w. Hence, they set prices as a mark-up over their real marginal costs

$$p_i = \frac{\eta}{\eta - 1}\frac{w_i}{z_i}(1 - \tau_w), \tag{H.1}$$

i.e., the wage subsidy raises the labor demand of each producer for each bundler that it is connected to. From this follows the gross profits as a function of connected bundlers:

$$\pi(\Theta_i, w_i) \quad = \quad \Theta_i \left(\frac{w_i}{z_i}\right)^{1-\eta} \bar{P}^{\eta} Y \frac{(\eta-1)^{\eta-1}}{\eta^{\eta}} (1-\tau_w)^{1-\eta}. \tag{H.2}$$

Moreover, using the wage equation, we can derive again wages as a function of the mass of connected bundlers as well as productivity and aggregates:

$$w_i = z_i^{\frac{(\eta-1)\hat{\omega}}{1+\eta\hat{\omega}}} \bar{w} \left(\frac{\Theta_i}{\bar{\Theta}}\right)^{\frac{\hat{\omega}}{1+\eta\hat{\omega}}} (1-\tau_w)^{-\frac{\eta\hat{\omega}}{1+\eta\hat{\omega}}}, \tag{H.3}$$

where $\bar{w} = \left[\left(\bar{P}\frac{\eta-1}{\eta}\right)^{\eta} \frac{Y}{l}\right]^{\frac{\hat{\omega}}{1+\eta\hat{\omega}}}$ summarizes the other aggregate terms that affect wages. Using (H.3) together with the gross profits, (H.2), and subtracting marketing expenditures yields the operating profits:

$$\Pi_i = \Theta_i \left(\frac{\Theta_i}{\bar{\Theta}}\right)^{\frac{\hat{\omega}}{1+\eta\hat{\omega}}(1-\eta)} z_i^{-(1-\eta)\frac{\hat{\omega}+1}{1+\eta\hat{\omega}}} \bar{P}^{\eta} Y \frac{(\eta-1)^{\eta-1}}{\eta^{\eta}} \bar{w}^{1-\eta} (1-\tau_w)^{\frac{1-\eta}{1+\eta\hat{\omega}}} - \mu \bar{P} \Theta_i. \tag{H.4}$$

Solving the associated first-order condition for Θ_i yields again a relationship between the optimal amount of connected bundlers and a producer's idiosyncratic productivity:

$$\frac{\Theta_i}{\bar{\Theta}} = z_i^{\frac{1+\hat{\omega}}{\hat{\omega}}} \left[\frac{Y}{\mu} \frac{1+\hat{\omega}}{1+\eta\hat{\omega}} \frac{1}{\eta} \left(\frac{\bar{P}}{\bar{w}} \frac{\eta-1}{\eta}\right)^{\eta-1}\right]^{\frac{1+\eta\hat{\omega}}{\hat{\omega}(\eta-1)}} (1-\tau_w)^{-\frac{1}{\hat{\omega}}}. \tag{H.5}$$

This equation, at first glance, seems to suggest that a wage subsidy indeed increases relative customer acquisition proportionally and for all firms. However, this is logically impossible, and thus, by using the definition of $\bar{\Theta}$, the subsidy term drops and we get back to the same equation (c.f. Equation (12)) that determines the individual producer's size of the customer network relative to the average:

$$\frac{\Theta_i}{\bar{\Theta}} = \left(\frac{z_i}{\bar{z}\phi} \phi^{-\frac{1}{\hat{\omega}}}\right)^{\frac{1+\hat{\omega}}{\hat{\omega}}}. \tag{H.6}$$

Using this equation, we can now derive the optimal producer-level behavior:

$$w_i = z_i \bar{w} \bar{z}^{-\frac{1+\hat{\omega}}{1+\eta\hat{\omega}}} \phi^{-\frac{(1+\hat{\omega})^2}{\hat{\omega}(1+\eta\hat{\omega})}} (1-\tau_w)^{\frac{-\eta\hat{\omega}}{1+\eta\hat{\omega}}}, \tag{H.7}$$

$$p_i = \frac{\eta}{\eta-1} \bar{w} \bar{z}^{-\frac{1+\hat{\omega}}{1+\eta\hat{\omega}}} \phi^{-\frac{(1+\hat{\omega})^2}{\hat{\omega}(1+\eta\hat{\omega})}} (1-\tau_w)^{\frac{1}{1+\eta\hat{\omega}}}, \tag{H.8}$$

$$\frac{p_i}{\bar{P}} = \frac{\hat{P}}{\bar{P}} = (\Gamma\bar{\Theta})^{\frac{1}{(\eta-1)}}, \tag{H.9}$$

$$l_i z_i = y_i = \left(\frac{p_i}{\bar{P}}\right)^{-\eta} Y = Y(\Gamma\bar{\Theta})^{\frac{\eta}{1-\eta}}. \tag{H.10}$$

From Equation (H.10), it follows that the distribution of output per bundler and, hence, employment per bundler is unchanged compared to the results in the main text. In particular, they do not depend on the wage subsidy. Together with Equation (H.6) this implies that the distribution of employment across plants, $l_i\Theta_i$, remains unchanged. Hence, the subsidy cannot cure the output loss resulting from reallocation of labor away from more to less productive producers.

It still could be that the subsidy promotes entry. The producers' free entry condition reads:

$$\int \Theta_i y_i \left(p_i - \frac{w_i}{z_i}(1-\tau_w)\right) di - \int \mu \bar{P} \Theta_i di = \lambda \bar{P}, \tag{H.11}$$

which, after aggregation and using Equations (H.7) - (H.10), yields:

$$\frac{Y}{\Gamma}\frac{1}{\eta} = \lambda + \mu\bar{\Theta}. \tag{H.12}$$

Similarly, we can derive again the average network size:

$$\bar{\Theta} = \frac{Y/\Gamma}{\mu}\frac{1}{\eta}\frac{1+\hat{\omega}}{1+\eta\hat{\omega}}, \tag{H.13}$$

where again τ_w does not show up explicitly.

Finally, labor market clearing implies that also Y is independent of τ_w, because

$$\Gamma \int \Theta_i l_i di = \Gamma \int z_i^{\frac{1}{\hat{\omega}}} Y (\Gamma\bar{\Theta})^{\eta/(1-\eta)} \bar{\Theta} \left(\frac{1}{\bar{z}\phi}\phi^{-\frac{1}{\hat{\omega}}}\right)^{\frac{1+\hat{\omega}}{\hat{\omega}}} di = 1 \tag{H.14}$$

yields for Y:

$$Y = \bar{z}\phi(\Gamma\bar{\Theta})^{\frac{1}{\eta-1}}\phi^{\frac{2}{\bar{\omega}}}. \tag{H.15}$$

This means that τ_w does not show up in any of the equilibrium conditions (H.12), (H.13), and (H.15), which are, therefore, the same as without the subsidy. This concludes the argument.

I A Subsidy on Business Network Investments

In Section 4, producers maximize profits given their private costs, μ, of acquiring an additional customer. Yet, individual private business investments create a positive externality by increasing the network size that producers build, and, thus, increase the productivity of the bundlers. This also means that all producers become more productive in producing final output. What is more, the increase in output increases aggregate demand leading to a yet larger optimal business network size. A Ramsey planner that can subsidize business network investments and thereby freely choose the networking costs, $\tilde{\mu}$, that private producers take into account, while the planner still has to pay the physical networking costs, μ, would maximize output minus real costs, i.e., consumption, which also equals labor compensation:

$$LC = Y - \Gamma(\lambda + \mu\bar{\Theta}), \tag{I.1}$$

subject to the optimal employment, customer acquisition, and entry decision of producers:

$$Y = \left(\frac{1}{\tilde{\mu}\eta}\frac{1+\hat{\omega}}{1+\eta\hat{\omega}}\right)^{\frac{1}{\eta-2}} \left(\phi^{\frac{2}{\hat{\omega}}}\right)^{\frac{1}{\eta-2}} \phi^{\frac{2}{\hat{\omega}}}, \tag{I.2}$$

$$\bar{\Theta} = \frac{\lambda}{\tilde{\mu}}\left[\frac{1}{\eta-1}\left(\frac{1+\hat{\omega}}{\hat{\omega}}\right)\right], \tag{I.3}$$

$$\Gamma = \frac{1}{\lambda}\frac{\eta-1}{\eta}\frac{\hat{\omega}}{1+\eta\hat{\omega}}Y. \tag{I.4}$$

Combining these equations yields:

$$LC = Y - Y\left(\frac{\eta-1}{\eta}\frac{\hat{\omega}}{1+\eta\hat{\omega}} + \frac{\mu}{\tilde{\mu}}\frac{1}{\eta}\frac{1+\hat{\omega}}{1+\eta\hat{\omega}}\right). \tag{I.5}$$

The corresponding first-order condition is given by:

$$\frac{\partial Y}{\partial\tilde{\mu}} - \frac{\partial Y}{\partial\tilde{\mu}}\left(\frac{\eta-1}{\eta}\frac{\hat{\omega}}{1+\eta\hat{\omega}} + \frac{\mu}{\tilde{\mu}}\frac{1}{\eta}\frac{1+\hat{\omega}}{1+\eta\hat{\omega}}\right) + \frac{1}{\tilde{\mu}^2}\frac{\mu}{\eta}\frac{1+\hat{\omega}}{1+\eta\hat{\omega}}Y = 0, \tag{I.6}$$

where, using (I.2),

$$\frac{\partial Y}{\partial \tilde{\mu}} = -\frac{1}{\eta - 2} Y \frac{1}{\tilde{\mu}}, \tag{I.7}$$

and, hence,

$$1 - \left(\frac{\eta - 1}{\eta} \frac{\hat{\omega}}{1 + \eta\hat{\omega}} + \frac{\mu}{\tilde{\mu}} \frac{1}{\eta} \frac{1 + \hat{\omega}}{1 + \eta\hat{\omega}} \right) - \frac{\mu}{\tilde{\mu}} \frac{\eta - 2}{\eta} \frac{1 + \hat{\omega}}{1 + \eta\hat{\omega}} = 0. \tag{I.8}$$

Rearranging yields:

$$\frac{\mu}{\tilde{\mu}} = \frac{\eta}{\eta - 1} \frac{1 + \hat{\omega}(\eta - \frac{\eta - 1}{\eta})}{1 + \hat{\omega}}. \tag{I.9}$$

That is, the optimal subsidy is positive $\left(\frac{\eta}{\eta-1} > 1 \text{ and } \frac{1+\hat{\omega}(\eta - \frac{\eta-1}{\eta})}{1+\hat{\omega}} > 1 \text{ if } \eta > 2 \right)$ and grows in $\hat{\omega}$.

However, the size-independent business network investment subsidy only addresses the business network size effect *sans* heterogeneity. It does not remedy the allocation of workers to relatively unproductive plants. This follows from the observation that the first-order condition is independent of the labor allocation effect, $\phi^{\frac{2}{\hat{\omega}}}$. By extension, the business network size effect *cum* heterogeneity, $\phi^{\frac{2}{\hat{\omega}} \frac{1}{\eta - 2}}$, is not remedied, either. In other words, a size-independent subsidy on business network investments cannot cure the output losses arising from the compressed distribution of labor across producers.