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This paper investigates how productivity dispersion relates to input misallocation using a model with staggered productivity shocks that create wedges between anticipated and realized productivity for any production input. With inputs allocated optimally ex ante but suboptimally ex post, dispersion in realized productivity contributes to ex post input misallocation. Analyzing European firm data from 2000–2017 reveals significant co-movement between productivity dispersion and capital/labor misallocation across industries. Productivity dispersion explains a substantial share of capital and labor misallocation (40% and 70%), and 10% of materials misallocation, confirming its key role in allocation frictions.

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1. Introduction

A firm's forecasted productivity informs key executive decisions about operations and investments. When leadership anticipates high productivity, they may increase orders for manufacturing inputs, expand staff and facilities, or allocate more funding to research and development for new products. Conversely, if lower productivity levels are projected, executives may opt for more conservative options to reduce costs and maintain profitability.

However, firms face dynamic uncertainty in forecasting future productivity. As productivity shocks occur unpredictably over time, initial forecasts may not match productivity levels. When wedges emerge between anticipated and realized productivity, input decisions set ex ante can significantly diverge from optimal ex post quantities, generating ex post misallocation even when choices are ex ante optimal. This paper investigates how productivity uncertainty drives misallocation across all production inputs when productivity shocks arrive at various stages of the firms' input decision timeline.

Aligning with established approaches, this analysis utilizes a standard metric—the dispersion of marginal revenue product (MRP) for an input across firms—to quantify ex post misallocation (Restuccia and Rogerson (2008), Hsieh and Klenow (2009)). Under certain assumptions, a non-negligible dispersion indicates the presence of frictions preventing resource flows from less to more efficient uses within an industry[1]. Notably, Asker, Collard-Wexler, and De Loecker (2014) show that for capital, a dynamic input

[1] Misallocative determinants include idiosyncratic regulations and institutions (Bartelsman, Haltiwanger, and Scarpetta (2009), Bartelsman, Haltiwanger, and Scarpetta (2013)), employment protection measures (Restuccia and Rogerson (2017)), credit supply shocks and financial frictions (Gopinath et al. (2017), Ben Zeev (2023)), sub-optimal endogenous firms' selection (Yang (2021)), factor adjustment costs and productivity information frictions (Asker, Collard-Wexler, and De Loecker (2014), David and Venkateswaran (2019)). Other determinants are noise introduced by measurement error (Gollin and Udry (2021), Bils, Klenow, and Ruane (2021)), production and demand heterogeneity (Restuccia and Rogerson (2013), Bento and Restuccia (2017), Blackwood et al. (2021), Haltiwanger, Kulick, and Syverson (2018)).

with adjustment costs, MRP dispersion and optimal allocations coexist because of heterogeneity in firms' productivity and adjustment frictions, even if a static view would imply suboptimality and misallocation due to the dispersion in MRP. This paper focuses specifically on how revenue total factor productivity (TFPR) idiosyncrasies and uncertainty generate MRP dispersion for any production input, expanding on David, Hopenhayn, and Venkateswaran (2016) by allowing imperfect information to impact all inputs and firms at various stages.

To infer the relationship between MRP and TFPR and its shock components, I estimate a partial equilibrium production function model based on Gandhi, Navarro, and Rivers (2020) using 2000-2017 European firm-level panel data, which I augment with time-varying TFPR processes to capture regime shifts due to the Financial Crisis.

The model treats capital and labor as predetermined relative to materials, a static input. It is agnostic to various dynamic and static distortions affecting input allocation, acknowledging historical evidence of European labor adjustment frictions post-2000. Productivity uncertainty is the sole explicitly modeled friction. The key feature is firms facing productivity shocks between allocating predetermined and materials inputs, as well as after materials. To the best of my knowledge, this is the first paper that disaggregates productivity shocks by timing and analyzes their distinct effects on input misallocation across all production inputs.

The model's micro estimates show input MRP dispersion increasing alongside TFPR dispersion, reflecting micro-level co-movement. Additionally, the Great Recession jointly raised TFPR dispersion while lowering mean TFPR across European sample countries. This evidences the crisis fundamentally curtailing aggregate productivity, rather than acting solely as a mean preserving spread as sometimes assumed in previous literature[2].

At the micro level, I find that capital and labor MRPs are the most sensitive to TFPR

[2] For a recent example, Arellano, Bai, and Kehoe (2019) assumed it for the US context.

variation, which explains a rising share of capital and labor misallocation over 2000-2017. By 2017, TFPR dispersion accounts for 40% of capital MRP dispersion and 70% of labor MRP dispersion on average. This confirms productivity as a primary misallocation driver for both factors, not just capital as predominantly focused on in past literature, with the relationship for labor even more pronounced. In contrast, the MRP of materials demonstrates weaker sensitivity to changes in TFPR. TFPR only accounts for 10% of materials misallocation over the sample period. However, decomposing TFPR reveals that materials MRP is highly sensitive to all its components, though their net aggregate impact is small. In particular, while some productivity components individually account for 25-35% of variation in materials MRP, ceteris paribus, these effects essentially offset one another at the aggregate level.

Overall, the results demonstrate that productivity idiosyncrasies account for a substantial proportion of input misallocation across countries and years. While some uncertainty is unavoidable, some policies and strategies[3] may help reduce the uncertainties firms face in decision-making. Failing to account for their impact on input misallocation could lead analysis to misattribute these effects to other distortions and propose misguided policy prescriptions.

The remainder of this paper is structured as follows. Section 2 presents the theoretical framework and derives the paper's testable predictions. Section 3 describes the data used and relevant descriptive statistics. Section 4 briefly discusses the empirical framework and identification/estimation strategy. Section 5 presents the main results, starting with stylized facts about the production technology estimates. It then shows the within-country co-evolution of MRP and TFPR dispersions. Next, it discusses the sensitivity of inputs' MRP to TFPR changes and the explanatory power of TFPR dispersion

[3]Examples include: stable trade and monetary policies; reducing variation in costs of doing business from regulations, healthcare, and taxes (Kang, Lee, and Ratti (2014), Gulen and Ion (2016)); ensuring efficient financial markets (Weill (2007)); and corporate strategies like lobbying and corporate social responsibility programs (Peng, Colak, and Shen (2023)).

for misallocation. It concludes by extending the analysis using a TFPR decomposition. Finally, Section 6 concludes with a discussion of limitations and suggestions for future research.

2. Theoretical Framework

The theoretical framework follows Gandhi, Navarro, and Rivers (2020), which I augment by including time-varying productivity processes. The framework incorporates firms' imperfect information around productivity as the sole explicit friction. Specifically, the model assumes multiple productivity shocks occurring between and after input allocations. The model remains intentionally agnostic on the allocation problem of capital and labor, assuming only they are predetermined relative to materials. This flexible approach allows the framework to generate dynamics consistent with a wide range of distortions that could impact these predetermined inputs in both static and intertemporal settings[4], while still focusing solely on productivity uncertainty as the key source of friction.

Let Y_{jt} the revenue and K_{jt}, L_{jt} and M_{jt} the capital, labor, and material inputs allocations of firm j at time t. Lowercase variables indicate natural logarithms. The log revenue function is non-parametrically specified as

$$y_{jt} = f(k_{jt}, l_{jt}, m_{jt}) + \nu_{jt} \tag{1}$$

Where ν_{jt} is revenue total factor productivity (TFPR), specified as the composition of a

[4]Examples are resale losses due to transaction costs, the market for lemons phenomenon (Akerlof (1970)), the physical cost of resale and refit costs for capital, hiring, firing, and training losses for workers (Bloom (2009)), working capital and borrowing constraints (see Camara and Sangiacomo (2022) for a discussion on their relevance for shocks propagation on an international perspective), government regulations, transportation costs, subsidies, and taxes (Hsieh and Klenow (2009)).

persistent and an unexpected component (Olley and Pakes (1996))

$$\nu_{jt} = \omega_{jt} + \varepsilon_{jt} \tag{2}$$

ω_{jt} is a persistent productivity factor that firm j perfectly observes at the beginning of period t but is unknown at time $t-1$. On the other hand, ε_{jt} represents a residual, short-term idiosyncratic revenue fluctuation observed only as the period ends [5].

Let $\mathfrak{I}_{jt}$ the information set that firm j holds at time t before the realization of ε_{jt}. Moreover, call $\tilde{\mathfrak{I}}_{jt}$ the information set that firm j holds at the end of period t. The following assumptions characterize the pricing behavior, the input allocation, the persistent productivity process, and the realization of the productivity shocks.

ASSUMPTION 1 (Pricing Behavior). *Firms are price takers in the output and input markets. The firm faces the nominal input prices w_{jt}, r_{jt}, and ρ_{jt} as the wage rate, the rental rate of capital, and the unit cost of materials. The input prices are paid simultaneously with each input allocation.*

ASSUMPTION 2 (Inputs Allocations). *Firm j allocates the period t capital and labor inputs, K_{jt} and L_{jt}, just before period t starts. Hence, these inputs are predetermined. On the other hand, the firm allocates intermediate materials, M_{jt}, after knowing ω_{jt} but before knowing ε_{jt} solving a static value-added maximization problem. Then, intermediate materials are a flexible production input.*

ASSUMPTION 3 (Persistent Productivity Process). *ω_{jt} follows a time-varying stochastic*

[5] Another observationally equivalent but conceptually distinct interpretation for ε_{jt} is the ex-post measurement error in the output. In this paper, I keep the interpretation in Gandhi, Navarro, and Rivers (2020) as a productivity forecast error. Additionally, following the convention in the production function estimation literature (Blum et al. (Forthcoming)), I assume no measurement errors in the input variables. Recent studies examining measurement errors in the capital input variable include Collard-Wexler and De Loecker (2016) and il Kim, Petrin, and Song (2016).

Markov process with a mean 0 forecast error that realizes in period t. Specifically,

$$\omega_{jt} = m_t(\omega_{jt-1}) + \eta_{jt}$$
$$\omega_{jt-1} \in \tilde{\mathfrak{I}}_{jt-1}, \quad \eta_{jt} \notin \tilde{\mathfrak{I}}_{jt-1}, \quad \eta_{jt} \perp \omega_{jt-1} \quad \forall j, t \tag{3}$$
$$E(\eta_{jt} \mid \tilde{\mathfrak{I}}_{jt-1}) = E(\eta_{jt}) = 0$$

where $m_t(.)$ is a continuous, strictly monotonic function, and η_{jt} is the forecast error that realizes in period t.

Notice that the forecast error η_{jt} is not necessarily identically distributed each period since the only restriction pertains to its first moment. Then, let its cross-sectional variance be time-variant, σ_t.

ASSUMPTION 4 (Productivity Shocks Realization Timing). *η_{jt} realizes at the beginning of period t. Then, the persistent productivity component, ω_{jt}, is known at the beginning of period t. The unexpected component, ε_{jt}, is an idiosyncratic, mean-independent, short-term output fluctuation and realizes towards the end of period t. Specifically,*

$$\omega_{jt} \in \mathfrak{I}_{jt}, \quad \varepsilon_{jt} \notin \mathfrak{I}_{jt}, \quad \varepsilon_{jt} \in \tilde{\mathfrak{I}}_{jt}, \quad \omega_{jt} \perp \varepsilon_{jt} \quad \forall j, t$$
$$E(\varepsilon_{jt} \mid \mathfrak{I}_{jt}) = E(\varepsilon_{jt}) = 0 \tag{4}$$
$$E(e^{\varepsilon_{jt}} \mid \mathfrak{I}_{jt}) = E(e^{\varepsilon_{jt}}) = \mathcal{E}$$

Where $\mathcal{E}$ is a scalar constant.

Again, the short-term fluctuation ε_{jt} is not necessarily identically distributed. Let its cross-sectional variance be time-variant, τ_t.

The following timeline summarizes the assumptions above

a. Firm j ends period $t-1$ knowing the period's TFPR ν_{jt-1} and the observed revenue Y_{jt-1}. That is, the firm has information set $\tilde{\mathfrak{I}}_{jt-1}$.

b. The firm now chooses L_{jt} and K_{jt} for nominal wage rate w_{jt} and rental rate of capital r_{jt}, as a function of $\tilde{\mathfrak{I}}_{jt-1}$.

c. Firm j enters period t. η_{jt} realizes. The firm now knows ω_{jt} and has information set $\mathfrak{I}_{jt}$.

d. The firm chooses the period t materials allocation, m_{jt}, as a function of $\mathfrak{I}_{jt}$ solving the following value-added maximization problem given the materials unit price ρ_{jt}

$$\max_{M_{jt}} \left[E(F(k_{jt}, l_{jt}, m_{jt}) e^{\nu_{jt}} \mid \mathfrak{I}_{jt}) - \rho_{jt} M_{jt} \right] \tag{5}$$

e. Finally, right before period t ends, the firm can now observe ε_{jt} and, then, the period's TFPR ν_{jt} and observed revenue Y_{jt}. The firm now has the information set $\tilde{\mathfrak{I}}_{jt}$.

Throughout this paper, I will consistently refer to η_{jt} as the *ex-ante productivity shock* and ε_{jt} as the *ex-post productivity shock*, relative to the material inputs allocation.

2.1. How Productivity Shocks Cause Misallocation

In this subsection, I show the mechanism through which productivity idiosyncrasies affect the marginal revenue product of the firm's inputs at the micro level. Thus, the dispersion in firm-level productivities generated by these idiosyncratic shocks translates into dispersion of input marginal revenue products across firms at the industry level, indicating misallocation.

The MRP of input X is the derivative of revenue Y with respect to input allocation X. By using the chain rule for derivative calculus, a simple decomposition expresses the marginal revenue product of any input X as a function of final revenue Y_{jt}, input allocation X_{jt}, and the revenue elasticity of that input $\frac{\partial y_{jt}}{\partial x_{jt}}$.

$$MRP_{jt}^{X} = \frac{\partial Y_{jt}}{\partial X_{jt}} = \frac{\partial Y_{jt}}{\partial y_{jt}} \frac{\partial x_{jt}}{\partial X_{jt}} \frac{\partial y_{jt}}{\partial x_{jt}} = \frac{Y_{jt}}{X_{jt}} elas_{jt}^{X} \quad \forall X \in \{K, L, M\} \tag{6}$$

Taking the natural logarithm, and totally differentiating[6] for TFPR leads to

$$\frac{dmrp_{jt}^{X}}{d\nu_{jt}} = \frac{dy_{jt}}{d\nu_{jt}} - \frac{dx_{jt}}{d\nu_{jt}} + \frac{d\log elas_{jt}^{X}}{d\nu_{jt}} \tag{7}$$

Equation (7) tells that three factors determine the elasticity of an input's marginal product concerning a hypothetical change in the firm's TFPR. The first and second terms are the revenue and input allocation elasticity to TFPR. Finally, the third term accounts for the effect of the change in TFPR on the input's revenue elasticity.

Notice now that, by combining equations (2) and (3), one can further decompose TFPR into three distinct components based on the firm's productivity information:

$$\nu_{jt} = m_t(\omega_{jt-1}) + \eta_{jt} + \varepsilon_{jt} \tag{8}$$

Then, using the chain and the inverse-function rules[7] , the total effect of a change in TFPR on the MRP of an input can be expressed as the combination of the effects of the

[6]Notice indeed that

$$\frac{\partial mrp_{jt}^{X}}{\partial y_{jt}} = -\frac{\partial mrp_{jt}^{X}}{\partial x_{jt}} = \frac{\partial mrp_{jt}^{X}}{\partial \log elas_{jt}^{X}} = 1$$

[7]Indeed

$$\frac{dmrp_{jt}^{X}}{d\nu_{jt}} = \left(\frac{d\nu_{jt}}{dmrp_{jt}^{X}}\right)^{-1} = \left(\frac{dm_t(\omega_{jt-1})}{dmrp_{jt}^{X}} + \frac{d\eta_{jt}}{dmrp_{jt}^{X}} + \frac{d\varepsilon_{jt}}{dmrp_{jt}^{X}}\right)^{-1}$$

$$= \left(\left(\frac{\S mrp_{jt}^{X}}{\S\omega_{jt-1}}\left(\frac{\partial m_t(\omega_{jt-1})}{\partial\omega_{jt-1}}\right)^{-1}\right)^{-1} + \left(\frac{\S mrp_{jt}^{X}}{\S\eta_{jt}}\right)^{-1} + \left(\frac{\S mrp_{jt}^{X}}{\S\varepsilon_{jt}}\right)^{-1}\right)^{-1}$$

The symbol § refers to a *partial total derivative*. For more details, I refer the reader to Wainwright and Chiang (2005), page 192. In this setup, $\frac{\S mrp^{X}}{\S\theta}$ has the interpretation of a total derivative keeping the other changes in each component of TFPR on that input's MRP. More formally,

$$\frac{dmrp_{jt}^{X}}{d\nu_{jt}} = c\left(\frac{dmrp_{jt}^{X}}{d\omega_{jt-1}}, \frac{dmrp_{jt}^{X}}{d\eta_{jt}}, \frac{dmrp_{jt}^{X}}{d\varepsilon_{jt}}\right) \tag{9}$$

In turn, each productivity driver effect can be decomposed in the usual way

$$\frac{dmrp_{jt}^{X}}{d\theta} = \frac{dy_{jt}}{d\theta} - \frac{dx_{jt}}{d\theta} + \frac{d\log elas_{jt}^{X}}{d\theta} \quad \forall\theta \in \{\omega_{jt-1}, \eta_{jt}, \varepsilon_{jt}\} \tag{10}$$

In summary, the theoretical framework outlined here predicts heterogeneous effects of past productivity, ex-ante productivity shocks, and ex-post productivity shocks on: 1) the firm's final revenue; 2) input allocations; and 3) the input's revenue elasticity. The sum effect of these pathways yields the total impact of TFPR variation on the MRP of a given input. Figure 1 summarizes this mechanism. Thus, at the aggregate industry level, productivity dispersion generates dispersion in input MRPs–indicating misallocation.

3. Data and Descriptive Statistics

Annual firm-level harmonized balance sheet data for European manufacturing (Nace Rev2 code C) firms in this paper are obtained from the MICROPROD project's Micro Data Infrastructure, hereafter MP[8]. Funded by the EU, MICROPROD integrates international

exogenous variables fixed. For example

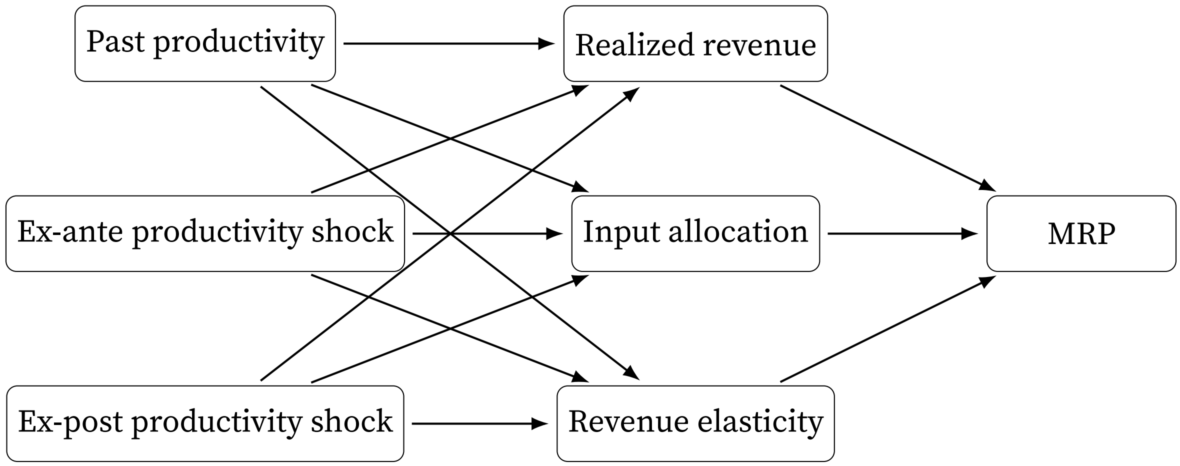
$$\frac{\S mrp_{jt}^{X}}{\S\omega_{jt-1}} = \left.\frac{dmrp_{jt}^{X}}{d\omega_{jt-1}}\right|_{d\eta_{jt}=0, d\varepsilon_{jt}=0}$$

However, since $\omega_{jt-1} \perp \eta_{jt} \perp \varepsilon_{jt}$ by assumptions 3 and 4, I can ease the notation by replacing the partial total derivatives with simple total derivatives

$$\frac{dmrp_{jt}^{X}}{d\nu_{jt}} = \left(\left(\frac{dmrp_{jt}^{X}}{d\omega_{jt-1}}\left(\frac{\partial m_t(\omega_{jt-1})}{\partial\omega_{jt-1}}\right)^{-1}\right)^{-1} + \left(\frac{dmrp_{jt}^{X}}{d\eta_{jt}}\right)^{-1} + \left(\frac{dmrp_{jt}^{X}}{d\varepsilon_{jt}}\right)^{-1}\right)^{-1}$$

[8] https://cordis.europa.eu/project/id/822390

FIGURE 1. How Productivity Shocks Cause Misallocation – Mechanism



European microdata to inform policymakers' growth and reform policies and assess economic functioning, based on Bureau van Dijk's ORBIS granular database.

As of 2020, MP contained 500,000 unique manufacturing firms for Italy, France, and Spain operating between 2000 and 2017. Additional German, Polish, and Romanian manufacturing firms operating between 2004 and 2018 have since been included. Critically, MP's careful examination of firm operating status[9], conservative imputation of missing values, and identification of a *productivity sample* minimally subject to imputation enables desirable representativeness by closely replicating Eurostat's aggregate Structural Business Statistics[10]. Altomonte and Coali (2020) extensively detail MP's data collection and cleansing. MP has seen some research use (Altomonte et al. (2021), Abele, Bénassy-Quéré, and Fontagné (2021), Altomonte et al. (2022)), while a host of studies have leveraged ORBIS directly (e.g. Asker, Collard-Wexler, and De Loecker (2014), Gopinath et al. (2017), Kalemli-Özcan et al. (Forthcoming)).

I use the variable *Operating Revenue (Turnover)* to approximate firm's revenue Y, and the *Number of Employees* to approximate the workforce L. MP does not have separate information on prices and quantities for the variables relative to intermediates and

[9] I.e., active or inactive
[10] `https://ec.europa.eu/eurostat/web/structural-business-statistics`

TABLE 1. Descriptive Statistics for Main Variables

Variable	Statistic	Germany	Spain	France	Italy	Poland	Romania
Operating Revenue, Th. Euros	Mean	82820	5305	14335	7209	18848	3246
	SD	682296	98994	263397	90308	96147	35602
	Median	19132	681	1201	1673	4137	160
	Q1	5390	261	399	679	1523	49
	Q3	53200	2063	4654	4562	11196	650
	Min	1	1	1	1	1	1
	Max	65336438	25537175	51905000	29382602	4818801	4990944
Cost of Materials, Th. Euros, Undeflated	Mean	51540	3459	7336	3945	12132	1936
	SD	1201597	85857	181084	68914	72588	27217
	Median	7946	305	331	644	2051	62
	Q1	1816	99	94	198	632	16
	Q3	25716	1073	1704	2077	6406	281
	Min	1	1	1	1	1	1
	Max	298700068	23475881	36833000	24205783	4239812	4192198
Fixed Assets, Th. Euros, Undeflated	Mean	23210	1980	3644	2284	7112	1516
	SD	177734	29474	98443	36201	42499	13156
	Median	2589	180	167	314	1034	41
	Q1	483	50	53	81	260	10
	Q3	9852	644	589	1164	3403	195
	Min	1	1	1	1	1	1
	Max	20739803	5867352	17469000	12144733	2420068	956784
Number of Employees	Mean	219	23	48	28	156	56
	SD	641	120	306	154	367	264
	Median	87	8	10	11	70	8
	Q1	32	4	4	5	26	3
	Q3	209	19	31	24	159	28
	Min	1	1	1	1	1	1
	Max	38383	17284	49425	33636	14600	18456
Observations		76403	1000134	606514	1261767	55581	168393

This table presents summary statistics for the key variables used in the analysis by country. The variables shown are *Operating Revenue*, a proxy for output (Y); *Cost of Materials*, a proxy for intermediates (M) after deflating; *Fixed Assets*, a proxy for capital (K) after deflating; and *Number of Employees*, a proxy for labor (L). The table displays the mean, standard deviation (SD), median, first and third quartiles (Q1 and Q3), minimum and maximum for each variable and country. The final row presents the sample size for each country.

working capital. Then, I resort to deflating the variables *Cost of Materials* for intermediates M, and *Total Fixed Assets* for capital K. I source industry-level (Nace Rev2 two digits) intermediate inputs (for materials) and gross output (for capital) deflators from EU-KLEMS.

Table 1 reports summary statistics for the main variables used in the analysis. From the first three quartiles (Q1, Median, and Q3), it is apparent that all variables distributions are heavily right-skewed, with many small firms and few big firms. The minima and maxima tell me that I capture both the tiny and the huge. However, from the comparison of medians and means across countries, it looks like the German and Polish firms samples still suffer from underrepresentativeness of smaller firms. This problem looks less prominent for the other countries.

4. Empirical Framework

Building on the nonparametric approach of Gandhi, Navarro, and Rivers (2020), I adapt the model estimation to allow for time-varying productivity dynamics. Additional details on this estimation procedure can be found in Appendix A.1.

Stage one involves manipulating the first-order firm maximization condition (5) to yield an estimable nonlinear equation. Applying least squares recovers two key outputs: materials revenue elasticities and firm-level ex-post productivity shocks. Integrating the estimated materials elasticity and subtracting it and the estimated shocks from revenue uncovers the sum of two unobserved components: the portion of revenue unrelated to materials and the persistent component of TFPR.

In stage two, polynomials approximate the Markov process for the persistent component of TFPR and the remaining part of the revenue function. Estimating the polynomial parameters uses generalized method of moments (GMM), exploiting orthogonality between past input allocations, persistent productivity, and ex-ante shocks. Validity of the nonparametric bootstrapped standard errors is discussed in Appendix A.1.1.

Ultimately, the model's estimates enable recovering firm-level input elasticities, marginal revenue products, and productivity components.

5. Results and Discussion

I let the productivity Markov process $m_t(.)$ vary across four historical periods: *Begin of the millennium* (2001–2003); *Pre-crisis* (2004–2007); *Great Recession and European debt crisis* (2008–2010); *Crisis aftermath* (2011–2013); and *Post-crisis* (2014–2017). Due to sample availability, productivity parameters for the period (2001–2003) are only available for Spain, France, and Italy. I estimate the production function for each country's industry by industry[11]. I compute standard errors via a non-parametric clustered bootstrap procedure, drawing with replacement from the pool of firms' identifiers 100 times. The model estimation results are reported in Appendix A.2. I now summarize the key findings.

The production function parameters are estimated precisely for all countries and industries represented in the sample. Across historical periods, the parameter estimates and standard errors for the Markov process ω_{jt} indicate it can be closely approximated by an AR(1) process with drift. The one exception is the German textile industry (Table A2), for which the AR(1) coefficients are negatively signed and imprecisely estimated. This divergence may originate from the small sample size for this industry (2,544 firms,

[11] Specifically, together with their Nace Rev2 codes they are

a. Food, beverages and tobacco (10, 11, and 12);
b. Textiles, apparel and leather (13, 14, and 15);
c. Wood, paper, and printing (16, 17, and 18);
d. Coke, chemicals, and pharmaceuticals (19, 20, 21);
e. Rubber, plastics, metallic and non-metallic mineral products, fabricated metal products (22, 23, 24, and 25);
f. Electronic, optical products and electrical equipment (26 and 27);
g. Machinery, motor vehicles and other transport equipment (28, 29, and 30);
h. Furniture and other manufacturing (31, 32, and 33).

merely 3% of the German sample), resulting in low statistical power.

More informative of the technological landscape than the production function parameters themselves are the estimated input revenue elasticities and returns to scale distributions, which are a functional of the model parameters[12]. Figure 2 plots the distribution densities of elasticities and returns to scale for each country, pooled across years and industries.

As expected, most revenue elasticity distributions lie within the unit interval. Notably, France and Germany display similar input intensities, with median[13] capital, materials, and labor elasticities of 0.17, 0.18, 0.58 and 0.15, 0.17, 0.67 respectively. Manufacturing in Italy and Spain relies more heavily on intermediates, with median materials elasticities of 0.28 and 0.41. Uniquely, Italy's labor elasticity distribution is double-peaked, possibly indicating twin low and high labor productivity equilibria. Romania's elasticities resemble Spain's but are slightly more capital-intensive. Finally, overlapping distributions suggest similar input intensities for Poland. Regarding returns to scale, Germany, France, Spain and Romania largely exhibit constant returns, with median values of 1.00, 0.96, 1.01 and 1.01 respectively, while Italy and Poland show decreasing returns at 0.88 and 0.92.

Overall, the model estimates paint a highly detailed, heterogeneous portrait of the six countries' manufacturing production economies. With this foundation established, we now turn our attention to the dispersion of the inputs' revenue marginal products and productivity, as well as their evolution over time.

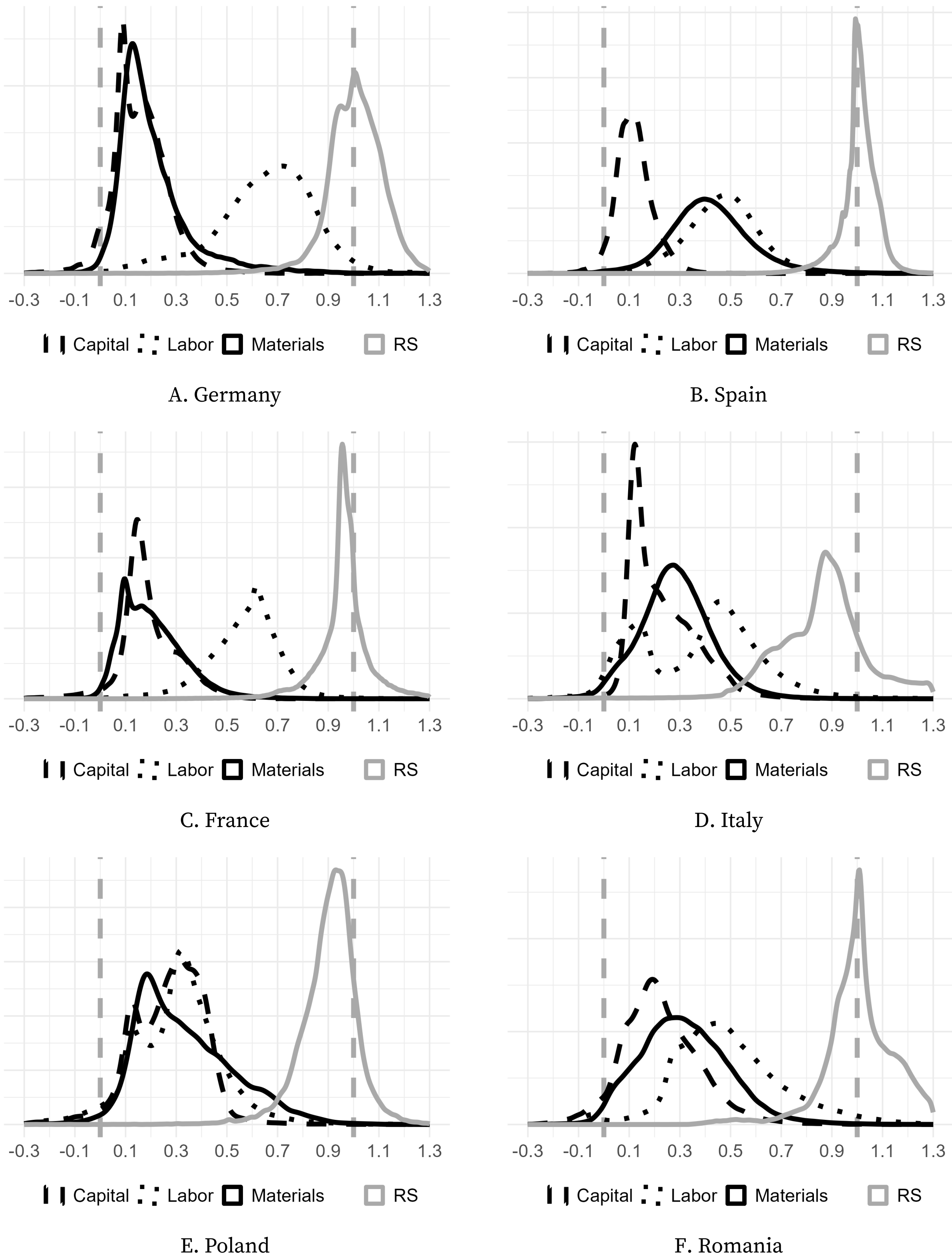
5.1. The (Co)Evolution of the Dispersions of Inputs MRP and TFPR

I generate aggregate (log) TFPR and MRP dispersion statistics for the manufacturing sector at the country-year level by taking the weighted average of the computed industry-

[12] For derivations of the firm-time specific elasticities, see the system of equations (A16). I compute firm-time specific returns to scale as the sum of the input elasticities.

[13] Because the distributions are highly skewed, I use the median as the measure of central tendency.

FIGURE 2. Revenue Elasticities and Returns to Scale Distributions



This figure displays the industry and time pooled distributions of estimated input revenue elasticities and returns to scale (RS) by country: Germany (Fig. 2A), Spain (Fig. 2B), France (Fig. 2C), Italy (Fig. 2D), Poland (Fig. 2E), and Romania (Fig. 2F). The inputs shown are materials (black solid line), capital (black dashed line), and labor (black dotted line). A solid grey line depicts the distribution of RS. The two dashed grey vertical lines delimit the interval $(0, 1)$.

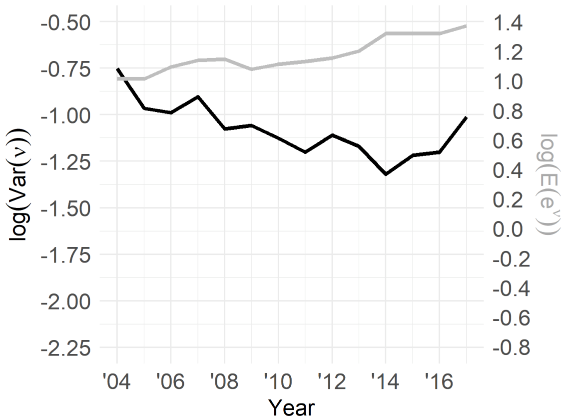
specific variances for these variables. The weights are time-invariant and equal to each industry's average annual share of manufacturing revenue. This approach reflects solely within-industry variation over time, as suggested in Gopinath et al. (2017). I plot the evolution over time of TFPR dispersion, as well as the average TFPR level, for each country in Figure 3. In Figure 4, I plot the evolution of aggregate dispersion for capital, labor, and materials MRP over time for each country.

The key insight from the figures is that MRP dispersion for capital, labor, and materials tends to move concurrently with TFPR dispersion within each country. As detailed in Section 2.1, this aligns with the micro-level relationship where firm-specific TFPR drives variation in MRPs. However, notable cross-country and cross-input differences exist in the scale of changes in MRP dispersion over time. This points to heterogeneous sensitivity in how shifts in TFPR affect marginal products across inputs and countries.

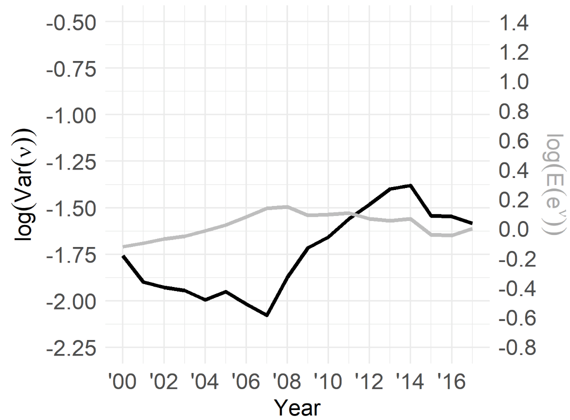
For instance, excluding Germany and Poland, rising TFPR dispersion coincided with the Great Recession for all sample countries, either gradually or suddenly. Mirroring this, capital MRP variance displays an overall increasing trajectory, accelerating especially in Spain, Italy, and Romania during the crisis. Labor and materials MRP variance exhibit less stable dynamics, with pre-crisis surges and later declines (e.g. Romania), abrupt crisis-induced spikes (e.g. Spain), or eventual reversed downturns after the crisis (e.g. Germany, France). Interestingly, Poland diverges slightly, as its sharp rises in TFPR and MRP dispersion occurred predominantly in the aftermath period rather than during the crisis like other countries. Nonetheless, some aggregate patterns emerge. The levels of labor and materials MRP dispersion remain smaller than capital in absolute terms, ranging from 20-75% of capital MRP variance by country over 2000–2017. Moreover, all inputs undergo higher rates of variance growth during and following the crisis.

A second key takeaway is that the Great Recession seemed to have changed both the dispersion and the aggregate means of TFPR across sample countries. Time trends display rising TFPR variance after 2008 coupled with declining mean TFPR *in levels*, ei-

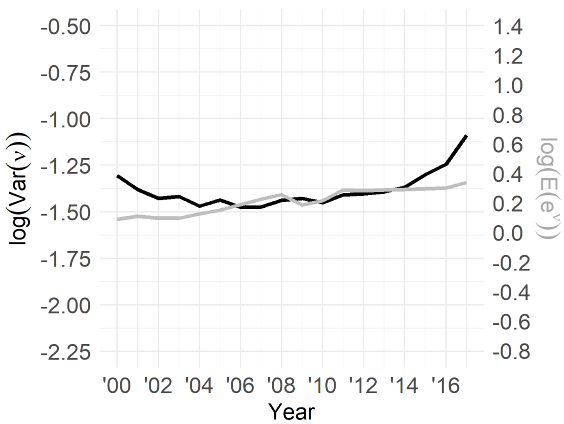
FIGURE 3. TFPR Dispersion and Mean Evolution



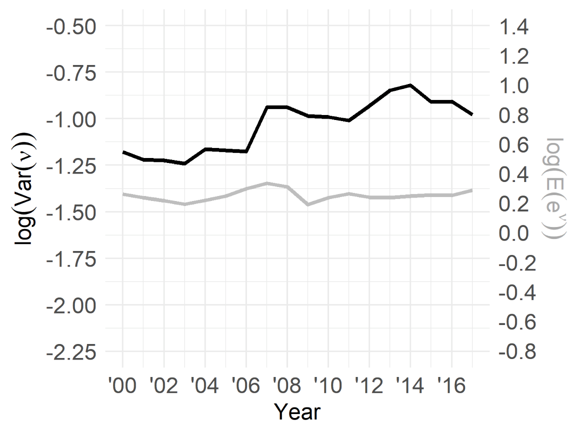
A. Germany



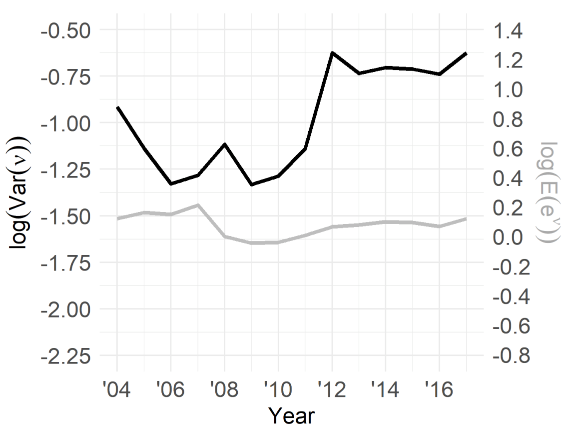
B. Spain



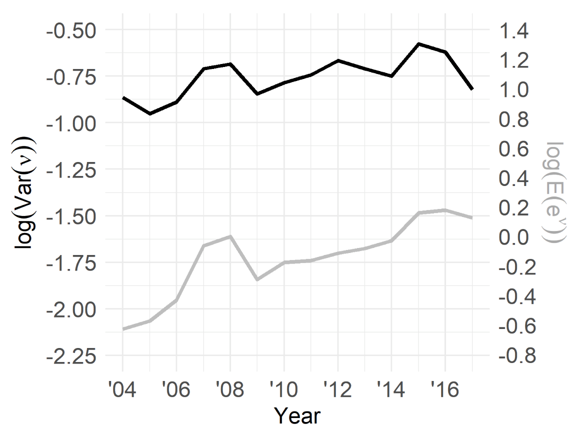
C. France



D. Italy



E. Poland



F. Romania

The solid black line in Figure 3 displays the evolution of the (log) aggregate variance for TFPR, ν, by country: Germany (Fig. 3A), Spain (Fig. 3B), France (Fig. 3C), Italy (Fig. 3D), Poland (Fig. 3E), and Romania (Fig. 3F). The solid gray line shows the (log) average value of TFPR *in levels*, reported on the secondary y-axis. I aggregate variances and means at the country level by taking a weighted average of the industry-specific variances and means, using average total manufacturing revenue shares for each industry as weights.

FIGURE 4. Inputs MRP Dispersions Evolution

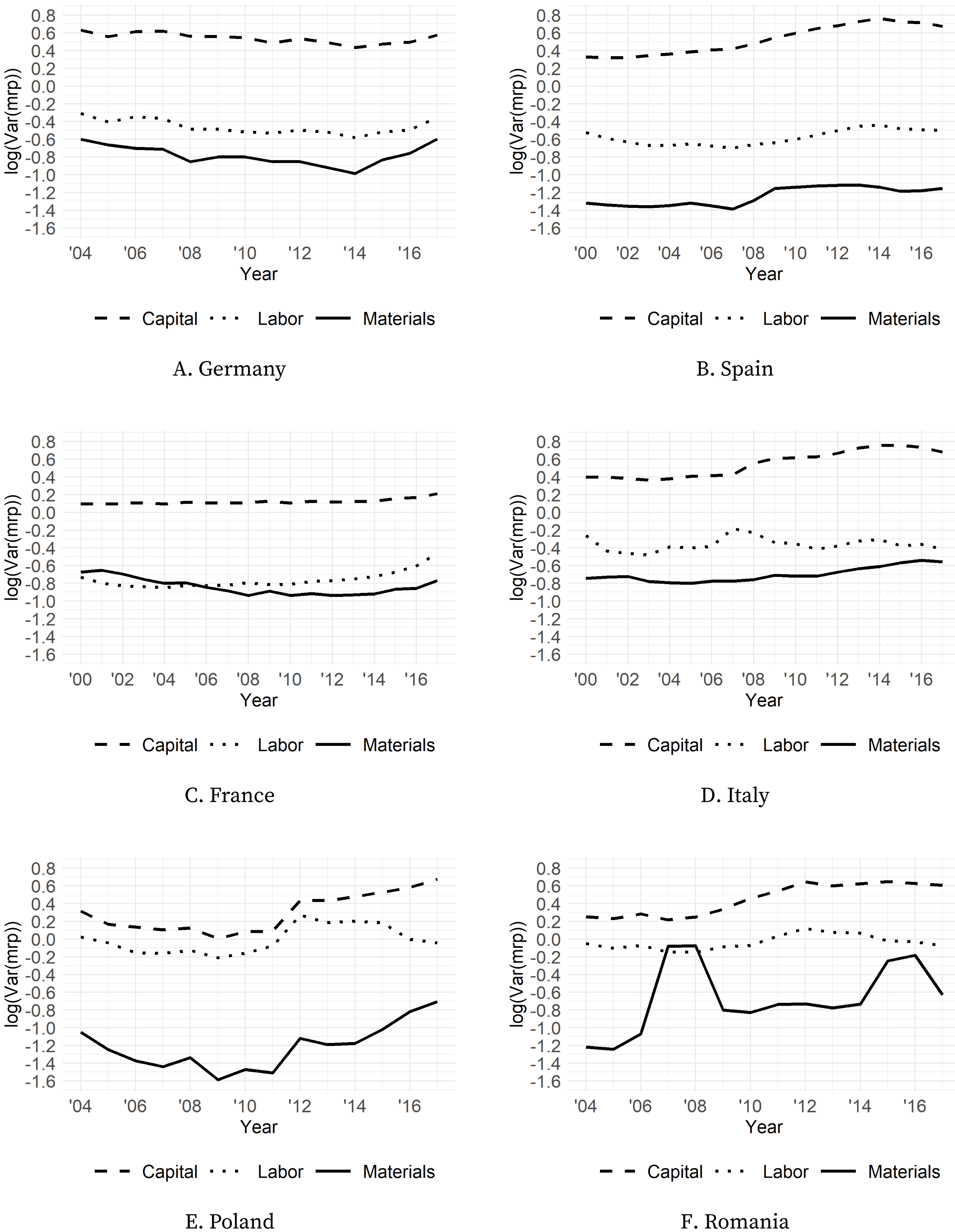


Figure 4 displays the evolution of the (log) aggregate variance for the inputs' log marginal revenue products by country: Germany (Fig. 4A), Spain (Fig. 4B), France (Fig. 4C), Italy (Fig. 4D), Poland (Fig. 4E), and Romania (Fig. 4F). The inputs shown are materials (solid black line), capital (dashed black line), and labor (dotted black line). I aggregate the log variances at the country level by taking a weighted average of the industry-specific variances, using the average shares in total manufacturing revenue for each industry as weights.

ther persistently or temporarily. Unlike a mean-preserving spread shock that maintains average productivity, this joint rise in dispersion and fall in averages indicates the crisis fundamentally depressed overall productivity while also increasing dispersion for the examined countries.

The analysis now turns to quantitatively assessing the sensitivity of the marginal revenue product of inputs to variations in TFPR. In other words, the focus is to quantitatively evaluate the mechanism described in Section 2.1.

5.2. Evaluating the Effect of a Change in TFPR on an Input MRP

In this section, I empirically assess the firm-level relationship between MRP and TFPR. I then quantify the macroeconomic implications of this relationship by examining the variation in MRP explained by the variation in TFPR at the industry level over time.

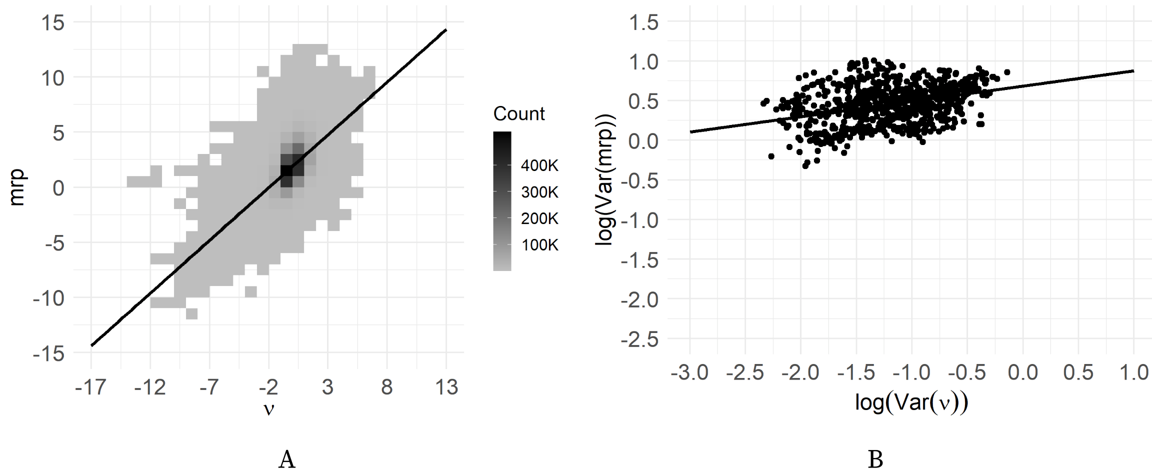
Figures 5, 6, and 7 provide initial visual evidence on the relationship between MRP and TFPR for each input using the full pooled dataset. Panels A show a binscatterplot of the log MRP for each input (y-axis) against TFPR (x-axis). The fitted linear regression line is displayed as a solid black line. For capital and labor, there appears to be an increasing relationship, with estimated slope coefficients of 0.96 and 0.79, respectively. The relationship looks weaker for materials, with a coefficient of 0.10.

In contrast, Panel B displays scatterplots of the log variance of log marginal revenue product (MRP) for each input (y-axis) against the log variance of TFPR (x-axis) at the country-industry-time level. The fitted linear regression line is also shown. An positive relationship emerges between industry-level dispersions of MRP and TFPR for all production inputs. This cross-sectional correlation appears stronger for labor and materials versus capital, with slope coefficients of 0.56 and 0.19, respectively.

The results in Figure 5 Panel B conceptually align with the capital-specific analysis in Figure 1 and Table 3 from Asker, Collard-Wexler, and De Loecker (2014)[14]. This paper

[14]My estimated slope coefficient of 0.19 is lower than the estimate reported by Asker, Collard-Wexler,

FIGURE 5. TFPR - MRP Correlation: Capital



Panel A displays a binscatterplot of the log marginal revenue product (MRP) for capital (y-axis) against TFPR (x-axis) for 3,168,792 firm-time observations. The color intensity indicates the number of observations per bin, with thousands indicated by "K" (see legend). The solid line is a fitted regression with a slope coefficient of 0.96. Panel B displays a scatterplot of the log variance of log MRP for capital (y-axis) against the log variance of TFPR (x-axis) for 768 country-industry-time observations. The solid line is a fitted regression with a slope coefficient of 0.19.

builds on their work by expanding the investigation to encompass all production inputs, including materials.

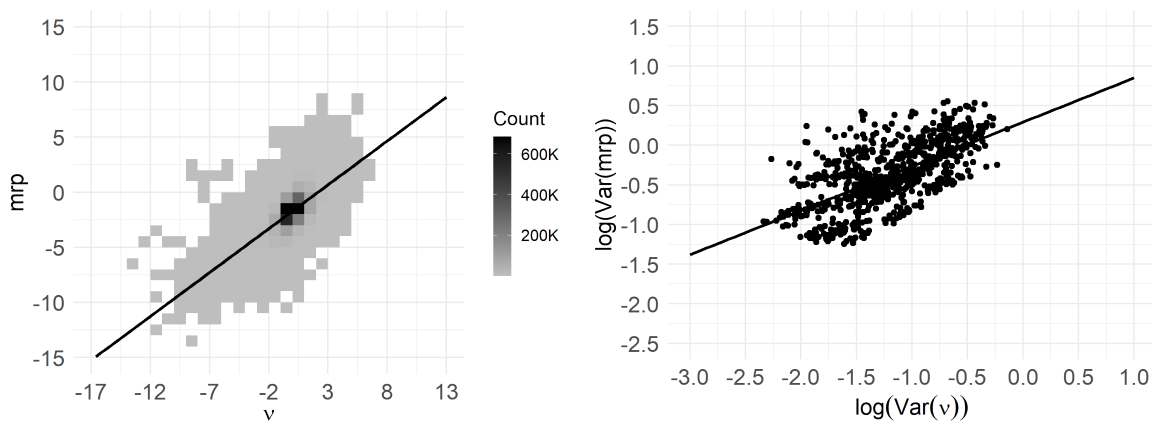
While these visualizations indicate evidence of correlation at the micro and macro level, a simple pooled linear regression has three key limitations. First, it fails to capture potentially heterogeneous sensitivity of MRP to TFPR shifts across countries and industries. Second, it does not quantify the proportion of MRP variation over time explained by industry-level TFPR variation. Finally, it does not examine heterogeneous impacts of specific TFPR shocks on MRP.

To address the first limitation, I estimate the relationship between MRP and TFPR for each country using the following linear models:

$$mrp_{jt}^{X} = c + \beta \nu_{jt} + \xi_{jt} \tag{11}$$

and De Loecker (2014). This divergence stems from several methodological factors: 1) the country sample differs, 2) industry definitions vary, 3) approaches estimating TFPR and capital's MRP contrast, and 4) the authors regress MRP dispersion on TFPR *volatility*, whereas I focus on TFPR *variance*.

FIGURE 6. TFPR - MRP Correlation: Labor



A B

Panel A displays a binscatterplot of the log marginal revenue product (MRP) for labor (y-axis) against TFPR (x-axis) for 3,168,792 firm-time observations. The color intensity indicates the number of observations per bin, with thousands indicated by "K" (see legend). The solid line is a fitted regression with a slope coefficient of 0.79. Panel B displays a scatterplot of the log variance of log MRP for labor (y-axis) against the log variance of TFPR (x-axis) for 768 country-industry-time observations. The solid line is a fitted regression with a slope coefficient of 0.56.

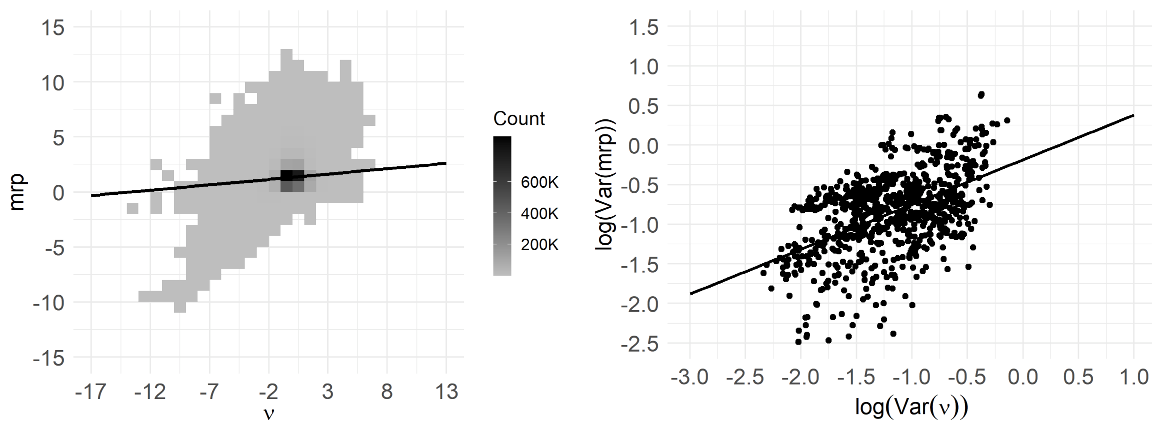
$$mrp_{jt}^{X} = \iota_{st} + \beta\nu_{jt} + \xi_{jt} \tag{12}$$

where mrp_{jt}^{X} is the MRP for input X and ν_{jt} is TFPR[15]. ξ_{jt} is the residual of the linear regression model. Model (11) is a simple linear regression, while model (12) adds industry-time fixed effects ι_{st}. For each model, the observations are weighted by the average industry revenue share of total manufacturing revenue. As the variables are both generated in a previous step, standard errors are computed using non-parametric clustered bootstrap resampling firms' identifiers. The regression results by country are reported in Table 2.

The coefficient β in both models estimates the average elasticity $\frac{dmrp_{jt}^{X}}{d\nu_{jt}}$ of MRP with respect to TFPR. The parameter estimates for the simple model (11) are highly statistically significant, especially for capital and labor. However, the estimated β increases in model (12) with industry-time fixed effects, indicating attenuation bias in model

[15] To avoid notational confusion, I will omit the hat symbol ($\hat{\cdot}$) for both the dependent and independent variables, even though they are estimated in a prior step.

FIGURE 7. TFPR - MRP Correlation: Materials



A B

Panel A displays a binscatterplot of the log marginal revenue product (MRP) for materials (y-axis) against TFPR (x-axis) for 3,168,792 firm-time observations. The color intensity indicates the number of observations per bin, with thousands indicated by "K" (see legend). The solid line is a fitted regression with a slope coefficient of 0.10. Panel B displays a scatterplot of the log variance of log MRP for materials (y-axis) against the log variance of TFPR (x-axis) for 768 country-industry-time observations. The solid line is a fitted regression with a slope coefficient of 0.56.

(11) from unobserved sector-specific effects. That is, the within industry-time variation shows a stronger MRP-TFPR correlation versus the pooled variation for a given country. This is expected since production technologies and shocks differ across sectors and years, creating omitted variable bias. With industry-time effects accounting for this, specification (12) is preferred.

Focusing on capital and labor, the elasticity estimates are large, precise, and relatively consistent across countries. For capital, estimates range around 1.25 for all countries except Spain (1.61). For labor, estimates are around 1.10 for all countries except Spain (1.28). In contrast, the preliminary weak MRP-TFPR relationship for materials is confirmed by lower β estimates. The highest values correspond to Spain (0.46), Romania (0.32), and Poland (0.10).

Interestingly, the elasticity of labor MRP to TFPR looks much more similar to capital than to materials. While a deeper investigation behind this result is outside the scope of this paper, one tentative implication is that labor allocation in these European countries

TABLE 2. TFPR Regression Results

	Germany		Spain		France		Italy		Poland		Romania	
Specification	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Capital												
β	0.395	1.226	1.567	1.608	1.167	1.279	0.892	1.238	0.496	1.210	1.098	1.276
	(0.021)	(0.026)	(0.008)	(0.008)	(0.008)	(0.009)	(0.004)	(0.007)	(0.015)	(0.019)	(0.008)	(0.008)
N	76403	76403	1000134	1000134	606514	606514	1261767	1261767	55581	55581	168393	168393
R^2	0.082	0.302	0.253	0.283	0.211	0.387	0.275	0.392	0.183	0.435	0.397	0.453
RMSE	1.272	1.109	1.162	1.138	1.008	0.889	1.167	1.069	1.109	0.922	1.026	0.977
Labor												
β	0.626	1.131	1.158	1.267	1.021	1.146	0.553	1.009	0.473	1.138	0.944	1.070
	(0.013)	(0.022)	(0.005)	(0.005)	(0.005)	(0.005)	(0.003)	(0.006)	(0.013)	(0.015)	(0.007)	(0.007)
N	76403	76403	1000134	1000134	606514	606514	1261767	1261767	55581	55581	168393	168393
R^2	0.400	0.699	0.497	0.568	0.584	0.734	0.200	0.525	0.091	0.535	0.530	0.636
RMSE	0.643	0.455	0.544	0.504	0.458	0.367	0.804	0.619	1.002	0.717	0.701	0.617
Materials												
β	-0.047	-0.101	0.541	0.456	0.008	-0.027	0.009	0.063	0.105	0.098	0.344	0.318
	(0.015)	(0.032)	(0.004)	(0.005)	(0.009)	(0.009)	(0.003)	(0.005)	(0.009)	(0.020)	(0.006)	(0.007)
N	76403	76403	1000134	1000134	606514	606514	1261767	1261767	55581	55581	168393	168393
R^2	0.000	0.017	0.144	0.195	-0.004	0.104	0.000	0.068	0.050	0.106	0.109	0.264
RMSE	0.688	0.683	0.538	0.522	0.736	0.695	0.763	0.736	0.598	0.580	0.814	0.740
Constant	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO
Industry-year FE	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES

The table presents regression results of the (log) MRP for each input on TFPR by country. Specification (1) refers to the simple linear model (11) and Specification (2) refers to the model with industry-year fixed effects (12). In both models, the observations are weighted by the industry average revenue share of total manufacturing revenue. Reported are the estimates for the slope coefficient (β), number of observations (N), unadjusted R^2, and root mean squared error (RMSE). Standard errors computed using clustered non-parametric bootstrap over 100 repetitions are in parentheses.

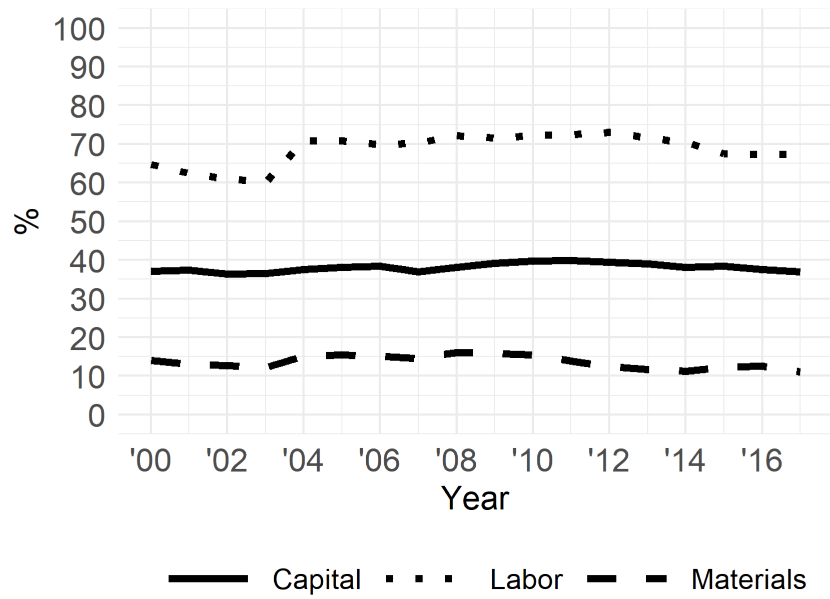
resembles capital investment behavior (Cooper and Haltiwanger (2006)) more than intermediate input adjustments, which firms can modify more flexibly.

To quantify the total proportion of input misallocation attributable to productivity dispersion, I use an industry-level regression approach. Specifically, I regress MRP of input X on TFPR for each country-industry pair over time, controlling for country-industry fixed effects. For each year, the regression model is:

$$mrp_{jt}^{X} = \iota_{cs} + \beta_{cs}\nu_{jt} + \xi_{jt} \tag{13}$$

where c here indicates country and s indicates sector. I then compute the unadjusted R^2 from this regression as a measure of how much productivity dispersion explains input misallocation across industries.

FIGURE 8. Proportion of MRP Dispersion Explained by TFPR Variation: R^2



This figure displays the average proportion of industry MRP dispersion explained by TFPR over time for each input. Specifically, I estimate the simple linear model in equation (13) for each input and year to compute the unadjusted R^2 values.

Figure 8 shows TFPR dispersion explains a sizable proportion of input misallocation over time. Overall, it accounts for 35-40% of capital misallocation. For labor, it starts at 60-65% in the early 2000s, reaching 70% in 2004 where it persists, indicating productivity dispersion primarily drives labor misallocation. While materials MRP and TFPR variances correlate (Figure 7 Panel B), TFPR only explains 10-15% of materials misallocation over 2000-2017. In summary, TFPR dispersion substantially explain capital and especially labor misallocation over time, but has less impact on materials misallocation.

My findings confirm and extend the results from Asker, Collard-Wexler, and De Loecker (2014), who showed that a calibrated model with capital adjustment costs and productivity volatility could explain 80-90% of the cross-industry variation in within-industry capital MRP dispersion. They were the first to identify productivity volatility as a key driver of capital MRP dispersion. This paper contributes to the literature by demonstrating that productivity dispersion accounts for MRP dispersion for all inputs.

The theoretical framework in Section 2.1 allows one additional contribution, which involves decomposing estimated TFPR into its three orthogonal components–past persistent productivity, ex-ante shocks, and ex-post shocks. Given the timing assumptions on input allocation, each input's MRP may have heterogeneous sensitivity to these different components. Additionally, the dispersion of the TFPR components may explain variation in industry-level MRP to different degrees across inputs. Investigating this heterogeneous relationship is the focus of the final results section.

5.3. Evaluating the Effect of a Change in TFPR Components on an Input MRP

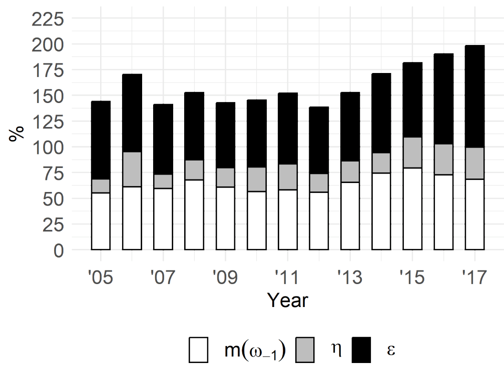
In this last section, the focus is twofold. First, I quantitatively assess the sensitivity of each input's MRP to the TFPR components from the decomposition in equation (8). Second, I compute the proportion of cross-sectional input MRP dispersion explained by the dispersion in each TFPR component.

The three TFPR components–past productivity, ex ante and ex post shocks–are assumed to be orthogonal in the theoretical model. Figure 9 plots histograms of the weighted average share of industry TFPR variance attributable to each component. The weights are each industry's average annual share of manufacturing revenue. If the components were fully orthogonal, these shares would sum to one each year.

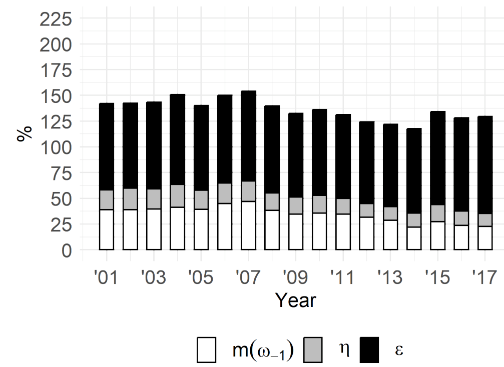
However, the observed sums deviating from one indicate there are non-zero covariances between the TFPR components at the industry level, pointing to correlated components in the data despite the theoretical assumption. Interestingly, the bulk of industry TFPR variation stems from ex-post productivity shocks ε, while ex-ante shocks η account for the least variation. Past persistent productivity ω_{-1} falls in between, explaining a moderate share on average.

Then, to study the heterogeneous sensitivity of input MRPs to TFPR components

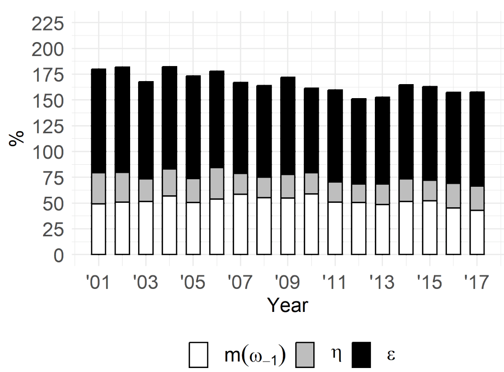
FIGURE 9. Component Share of TFPR Variance



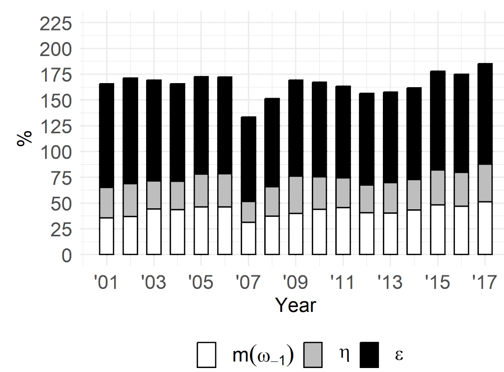
A. Germany



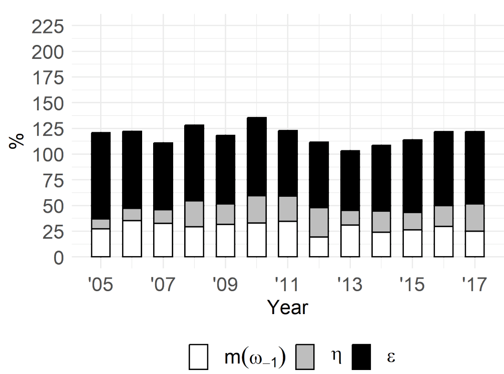
B. Spain



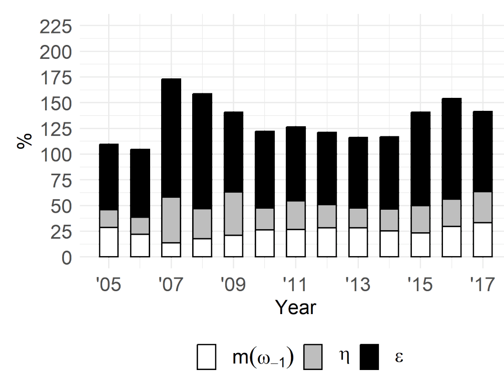
C. France



D. Italy



E. Poland



F. Romania

This Figure shows the annual weighted average share of industry-year TFPR variance attributable to each TFPR component from the decomposition in equation (8), for each country. The weights are each industry's average share of total annual manufacturing revenue in that country.

across countries, while avoiding omitted variable bias, I estimate the following linear models separately for each country:

$$mrp_{jt}^{X} = c + \beta_{\omega_{-1}}\omega_{jt-1} + \beta_{\eta}\eta_{jt} + \beta_{\varepsilon}\varepsilon_{jt} + \xi_{jt} \tag{14}$$

$$mrp_{jt}^{X} = \iota_{st} + \beta_{\omega_{-1}}\omega_{jt-1} + \beta_{\eta}\eta_{jt} + \beta_{\varepsilon}\varepsilon_{jt} + \xi_{jt} \tag{15}$$

where mrp_{jt}^{X} is the MRP for input X, ω_{jt-1} is past persistent productivity component, η_{jt} is the ex-ante shock, ε_{jt} is the ex-post shock, and ξ_{jt} is the model's residual. Model (15) adds industry-year fixed effects ι_{st}. I standardize the variables to make their scales comparable. Observations are weighted by average annual industry revenue shares. Standard errors are computed by individual-level clustered bootstrap, given the first-stage generated variables. The results by country are in Table 3.

The coefficients $\beta_{\omega_{-1}}$, β_{η}, and β_{ε} estimate the average elasticities $\frac{d\mathrm{mrp}_{jt}^{X}}{d\omega_{jt-1}}$, $\frac{d\mathrm{mrp}_{jt}^{X}}{d\eta_{jt}}$, and $\frac{d\mathrm{mrp}_{jt}^{X}}{d\varepsilon_{jt}}$ respectively. Specifically, since numerators and denominators are normalized, they estimate the average percentage change in MRP measured in units of standard deviations, for a one percent standard deviation change in each of those variables, holding the others constant.

Importantly, the slope coefficients from the MRP regressions for capital and labor increase overall, while decreasing for materials, after controlling for industry-year fixed effects. Moreover, the estimated coefficients become more homogeneous across countries, while retaining high statistical significance. These findings suggest specification (1) suffers from bias stemming from unobserved sector-specific effects. Additionally, it indicates industry heterogeneity plays a more important role than country heterogeneity in determining the marginal effects of TFPR components on an input's MRP. For these reasons, I take specification (2) with industry-year fixed effects as the baseline.

TABLE 3. TFPR Components Regression Results

	Germany		Spain		France		Italy		Poland		Romania	
Specification	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Capital												
$\beta_{\omega_{-1}}$	0.117	0.505	0.749	0.839	0.497	0.558	0.310	0.426	0.126	0.439	0.354	0.436
	(0.010)	(0.016)	(0.007)	(0.009)	(0.006)	(0.009)	(0.002)	(0.005)	(0.007)	(0.015)	(0.006)	(0.008)
β_{η}	0.235	0.265	0.381	0.380	0.270	0.273	0.278	0.287	0.256	0.261	0.273	0.276
	(0.010)	(0.009)	(0.004)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.011)	(0.010)	(0.004)	(0.004)
β_{ε}	0.370	0.490	0.541	0.545	0.458	0.471	0.490	0.519	0.434	0.461	0.466	0.480
	(0.022)	(0.017)	(0.004)	(0.004)	(0.005)	(0.006)	(0.003)	(0.003)	(0.012)	(0.011)	(0.004)	(0.004)
N	76403	76403	1000134	1000134	606514	606514	1261767	1261767	55581	55581	168393	168393
R^2	0.325	0.455	0.346	0.380	0.307	0.450	0.422	0.476	0.459	0.559	0.513	0.544
RMSE	0.902	0.810	0.852	0.829	0.741	0.660	0.819	0.780	0.728	0.658	0.748	0.724
Labor												
$\beta_{\omega_{-1}}$	0.347	0.661	0.661	0.826	0.615	0.721	0.263	0.580	0.177	0.592	0.447	0.543
	(0.010)	(0.027)	(0.006)	(0.009)	(0.005)	(0.007)	(0.003)	(0.008)	(0.010)	(0.027)	(0.009)	(0.013)
β_{η}	0.303	0.328	0.441	0.457	0.332	0.339	0.271	0.295	0.334	0.341	0.345	0.347
	(0.008)	(0.011)	(0.004)	(0.005)	(0.003)	(0.003)	(0.002)	(0.003)	(0.012)	(0.011)	(0.005)	(0.006)
β_{ε}	0.464	0.554	0.599	0.607	0.552	0.576	0.358	0.436	0.532	0.561	0.514	0.521
	(0.014)	(0.019)	(0.003)	(0.003)	(0.004)	(0.004)	(0.002)	(0.002)	(0.014)	(0.013)	(0.005)	(0.005)
N	76403	76403	1000134	1000134	606514	606514	1261767	1261767	55581	55581	168393	168393
R^2	0.569	0.747	0.562	0.631	0.636	0.757	0.386	0.623	0.386	0.607	0.613	0.685
RMSE	0.626	0.480	0.553	0.507	0.467	0.382	0.769	0.603	0.924	0.739	0.717	0.647
Materials												
$\beta_{\omega_{-1}}$	-0.186	-0.484	0.086	-0.245	-0.412	-0.573	-0.241	-0.436	-0.041	-0.347	-0.154	-0.338
	(0.007)	(0.028)	(0.004)	(0.007)	(0.009)	(0.013)	(0.002)	(0.005)	(0.005)	(0.019)	(0.006)	(0.010)
β_{η}	-0.122	-0.149	-0.105	-0.140	-0.108	-0.119	-0.074	-0.087	-0.088	-0.095	-0.073	-0.083
	(0.010)	(0.010)	(0.006)	(0.006)	(0.007)	(0.007)	(0.002)	(0.003)	(0.012)	(0.011)	(0.006)	(0.006)
β_{ε}	0.599	0.512	0.645	0.638	0.546	0.512	0.425	0.385	0.541	0.515	0.576	0.543
	(0.018)	(0.021)	(0.005)	(0.004)	(0.008)	(0.009)	(0.004)	(0.004)	(0.020)	(0.019)	(0.007)	(0.007)
N	76403	76403	1000134	1000134	606514	606514	1261767	1261767	55581	55581	168393	168393
R^2	0.623	0.719	0.452	0.609	0.486	0.617	0.488	0.602	0.563	0.717	0.504	0.656
RMSE	0.656	0.567	0.632	0.535	0.775	0.669	0.805	0.710	0.614	0.495	0.925	0.770
Constant	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO
Industry-year FE	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES

The table presents regression results of the (log) MRP for each input on TFPR components by country. Specification (1) refers to the simple linear model (14) and Specification (2) refers to the model with industry-year fixed effects (15). In both models, the observations are weighted by the industry average revenue share of total annual manufacturing revenue. Reported are the standardized estimates for the component-specific slope coefficients ($\beta_{\omega_{-1}}$, β_{η}, β_{ε}), number of observations (N), unadjusted R^2, and root mean squared error (RMSE). Standard errors computed using clustered non-parametric bootstrap over 100 repetitions are in parentheses.

For the capital MRP, lagged productivity (ω_{-1}) and the ex-post shock (ε) demonstrate the highest sensitivity, with elasticities ranging from 0.43 in Italy to 0.84 in Spain for the former and from 0.46 in Poland to 0.55 in Spain for the latter. Regarding the labor MRP, the sensitivity to the ex-post shock and lagged productivity is similar in magnitude to that for capital, indicating parallels in the nature of these two inputs. The elasticity with respect to the ex-post shock spans 0.44 in Italy to 0.61 in Spain, averaging around 0.50 across other sample countries, while for past productivity it ranges from 0.54 in Romania to 0.83 in Spain.

Both capital and labor MRPs show the lowest sensitivity to the ex-ante productivity shock (η). For capital, the average standardized elasticities range from 0.26 in Germany and Poland to 0.38 in Spain. For labor MRP, the elasticity to the ex-ante shock is slightly higher, ranging from 0.30 in Italy to 0.46 in Spain, with values around 0.33-0.34 in remaining countries.

Materials warrant a separate discussion. The results show a puzzling, *negative* sensitivity of materials MRP to past productivity and the ex-ante productivity shock, ranging from -0.25 in Spain to -0.57 in France for the first and from -0.08 in Romania to -0.15 in Germany for the second.

A tentative explanation is as follows. Given the timeline assumptions, firms know the past productivity ω_{-1} and ex-ante shock η components before allocating material inputs, which directly enter the firms' decision problem (equation (5)). Input and output markets are competitive and materials are flexible inputs–firms equate expected MRP to marginal cost in expectation. Assuming fixed nominal output and input prices, higher known productivity means firms require fewer material input units for the same marginal output. Thus, the marginal cost of additional revenue falls. By equilibrium, the MRP of materials must decrease as well.

Since firms allocate materials before realizing the ex-post productivity shock ε, its effect on materials MRP is unrestrained by equilibrium conditions. Accordingly, results demonstrate the expected positive effect, spanning 0.38 in Italy to 0.64 in Spain.

The presence of a strongly negative, statistically significant sensitivity of materials MRP to ω_{-1} and η alongside a strongly positive, statistically significant sensitivity to ε explains the preliminary weak correlation in Figure 7 Panel A. It also accounts for the weak or null results when regressing materials MRP on TFPR in Table 2. These outcomes owe to the offsetting effects of the individual components.

I quantify the degree of input misallocation (measured by cross-sectional industry dispersion in inputs' MRP) attributable to each TFPR component by using the coefficient of partial determination (partial R^2). Specifically, for each input and year, I first estimate the *full* regression model in equation (16) by regressing the inputs' MRP on each TFPR component and allowing the slope coefficients to vary by country-industry pair, including country-industry fixed effects. I then record the unadjusted R^2.

$$mrp_{jt}^{X} = \iota_{cs} + \beta_{\omega_{-1},cs}\omega_{jt-1} + \beta_{\eta,cs}\eta_{jt} + \beta_{\varepsilon,cs}\varepsilon_{jt} + \xi_{jt} \tag{16}$$

Next, for each TFPR component $\theta_{jt} \in \{\omega_{jt-1}, \eta_{jt}, \varepsilon_{jt}\}$, I re-estimate the model excluding that particular regressor θ_{jt} to obtain *reduced* model unadjusted R^2 values.

The partial R^2 for each TFPR component θ[16] is then calculated as:

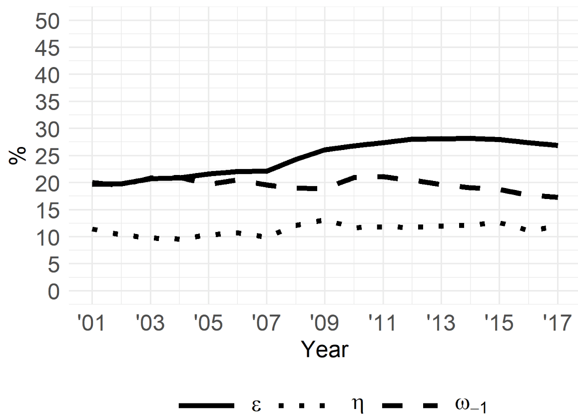
$$R^2(\theta) = \frac{R^2_{\text{full}} - R^2_{\text{reduced},\theta}}{1 - R^2_{\text{reduced},\theta}} \tag{17}$$

where R^2_{full} is from the full model and $R^2_{\text{reduced},\theta}$ comes from the regression excluding θ_{jt}. The interpretation of $R^2(\theta)$ is the additional percentage of the cross-sectional, country- and industry-specific variation in the input's MRP explained by component θ_{jt}, given the other TFPR components.

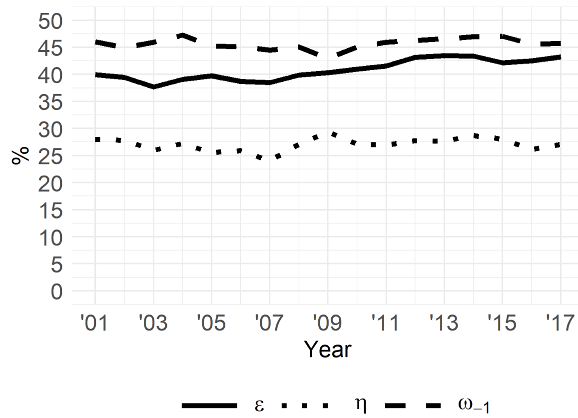
Figure 10 shows the results. For capital and labor, most of the input MRP dispersion is explained by variation in the ex-post productivity shock ε and past persistent productivity ω_{-1}. The ex-post shock explanatory power for capital rose from 20% in 2001 to 30% in 2017, accelerating post-Recession, while remaining around 40% for labor. The past productivity explanatory power was steadier - around 20% for capital and 45% for

[16]For conciseness, the notation for the partial R^2 depends only on θ, but the statistic is computed separately for each input and year.

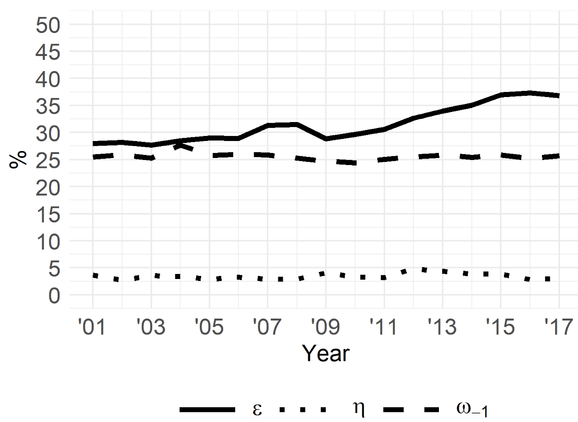
FIGURE 10. Proportion of MRP Dispersion Explained by TFPR Components Variation: Partial R^2



A. Capital



B. Labor



C. Materials

This figure shows the average proportion of industry variation in MRP explained by each TFPR component, holding other components fixed. Specifically, I estimate the input-, year-specific $R^2(\theta)$ values using equation (17) for each TFPR component $\theta_{jt} \in \{\omega_{jt-1}, \eta_{jt}, \varepsilon_{jt}\}$.

labor. The ex-ante productivity shock η explained less MRP variation (10% for capital, 25-30% for labor).

Regarding materials' MRP variation, the lion's share is explained by the ex-post productivity shock, starting at around 30% and peaking at 37% in 2015. The explanatory power of past persistent productivity is steady around 25%. Finally, for the ex-ante shock η it fluctuates around 5% over the sample period.

These last values seem at odds with Figure 8, where total TFPR explains almost no dispersion in materials' MRP. However, recall from Table 3 that materials MRP sensitivity to η and ω_{-1} is negative, while sensitivity to ε is positive. Thus, variation in TFPR components in the same direction has a muted net marginal effect on materials' MRP, reconciling the findings. Although individual components may substantially explain materials' MRP dispersion, their offsetting signs mean total TFPR exhibits negligible explanatory power.

6. Summary and Concluding Remarks

To my knowledge, this is the first paper to analyze the link between different sources of productivity shocks and input misallocation, measured by MRP dispersion, across all production inputs. The paper confirms the established relationship in literature between productivity uncertainty and capital misallocation. Moreover, I demonstrate that the strength of this relationship depends on the specific timing of productivity shocks. Further, the relationship heterogeneously generalizes to all inputs, with labor bearing high similarities to capital, indicating comparable allocation mechanisms for these inputs in the countries and timeframe studied.

The analysis revealed several key findings. First, MRP dispersion for all inputs significantly co-moves with TFPR dispersion. The data also show the Great Recession simultaneously increased TFPR dispersion and reduced productivity. Second, capital and especially labor MRP have high sensitivity to firm-specific productivity changes, with TFPR dispersion explaining 40% and 70%, respectively, of their misallocation over time–confirming it as a key driver. Finally, decomposing TFPR shows inputs react heterogeneously to its components, and offsetting shock sensitivities mute the aggregate relationship between productivity dispersion and materials misallocation.

In conclusion, productivity idiosyncracies substantially contribute to input misallocation among firms. While some productivity uncertainty is inevitable, policies promoting stability and efficiency may curb misallocation. Moreover, accounting for productivity uncertainty is critical to precisely quantify the effect of other distortions on input misallocation.

This framework has limitations that present opportunities for future research. First, it does not account for heterogeneous market power, an influential factor on marginal product dispersion. In addition, balancing the strengths of this partial equilibrium approach with modeling specific misallocation drivers like adjustment costs and taxes is an important next step. Overcoming these limitations could further illuminate the respective roles of productivity and other distortions in generating marginal revenue product dispersion. This could provide a more complete understanding of the fundamental causes of, and optimal policy responses to, input misallocation.

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Appendix A.

A.1. Identification and Estimation of the Partial Equilibrium Model (Gandhi, Navarro, and Rivers (2020))

Taking the FOC for M_{jt} in equation (5) yields

$$\frac{\partial E(F(k_{jt}, l_{jt}, m_{jt})e^{\nu_{jt}} \mid \mathcal{I}_{jt})}{\partial M_{jt}} - \rho_{jt} = 0 \tag{A1}$$

By the distributional assumptions on ω_{jt} and ε_{jt} (see assumptions 3 and 4), the FOC reads

$$\frac{\partial F(k_{jt}, l_{jt}, m_{jt})}{\partial M_{jt}} e^{\omega_{jt}} \mathcal{E} - \rho_{jt} = 0 \tag{A2}$$

Taking logs, and substituting $\omega_{jt} = y_{jt} - f(k_{jt}, l_{jt}, m_{jt}) - \varepsilon_{jt}$ delivers

$$\log(\rho_{jt}) = \log(Y_{jt}) - f(k_{jt}, l_{jt}, m_{jt}) - \varepsilon_{jt} + \log \mathcal{E} + \log \frac{\partial F(k_{jt}, l_{jt}, m_{jt})}{\partial M_{jt}} \tag{A3}$$

Let $s_{jt} = \log\left(\frac{\rho_{jt} M_{jt}}{Y_{jt}}\right)$, the (log) intermediates cost share of revenue of firm j at time t. Rearranging [17] equation (A3) yields an expression of the log intermediates share as a function of the log revenue elasticity of intermediate inputs, a scalar constant, and the

[17]Indeed, notice that

$$\begin{aligned}
&\log \frac{\partial F(k_{jt}, l_{jt}, m_{jt})}{\partial M_{jt}} - f(k_{jt}, l_{jt}, m_{jt}) \\
&= \log \frac{\partial F(k_{jt}, l_{jt}, m_{jt})}{\partial M_{jt}} - \log F(k_{jt}, l_{jt}, m_{jt}) \\
&= \log \left(\frac{\partial F(k_{jt}, l_{jt}, m_{jt})}{F(k_{jt}, l_{jt}, m_{jt})} / \frac{\partial M_{jt}}{M_{jt}} \right) - \log M_{jt} \\
&= \log \left(\frac{\partial f(k_{jt}, l_{jt}, m_{jt})}{\partial m_{jt}} \right) - m_{jt}
\end{aligned} \tag{A4}$$

ex-post productivity shock

$$s_{jt} = \log\left(\frac{\partial f(k_{jt}, l_{jt}, m_{jt})}{\partial m_{jt}}\right) + \log \mathcal{E} - \varepsilon_{jt} \tag{A5}$$

The intermediate inputs elasticity $\frac{\partial f(k_{jt}, l_{jt}, m_{jt})}{\partial m_{jt}}$ can be approximated using a second degree, complete polynomial in capital, labor, and material inputs allocations.

Then, substituting it into equation (A5) yields

$$s_{jt} = \log\left(\begin{array}{c} \gamma_0 + \gamma_k k_{jt} + \gamma_l l_{jt} + \gamma_m m_{jt} + \gamma_{kk} k_{jt}^2 + \gamma_{ll} l_{jt}^2 \\ + \gamma_{mm} m_{jt}^2 + \gamma_{kl} k_{jt} l_{jt} + \gamma_{km} k_{jt} m_{jt} + \gamma_{lm} l_{jt} m_{jt} \end{array}\right) + \log \mathcal{E} - \varepsilon_{jt} \tag{A6}$$

The γ parameters in equation (A6) can be consistently estimated via non-linear least square up to the scalar constant $\mathcal{E}$. Call $\hat{\gamma}'$ this estimate[18]. However, since the (negative) regression residuals are estimates for the ex-post productivity forecast error ε_{jt}, by assumption 4, one can use them to estimate $\hat{\mathcal{E}} = \frac{1}{JT} \sum_{(j,t)} e^{\hat{\varepsilon}_{jt}}$.

Then, having an estimate for $\mathcal{E}$, one can recover an estimate[19] $\hat{\gamma}$ for the parameters vector free of the constant $\mathcal{E}$ and, then, an estimate for the intermediate input elasticity, $\frac{\partial f(k_{jt}, l_{jt}, m_{jt})}{\partial m_{jt}}$.

Finally, one can estimate the cross-sectional variance τ_t by taking the cross-sectional

---

Where the last equality follows from $\frac{\partial F(k_{jt}, l_{jt}, m_{jt})}{F(k_{jt}, l_{jt}, m_{jt})} / \frac{\partial M_{jt}}{M_{jt}} = \frac{\partial f(k_{jt}, l_{jt}, m_{jt})}{\partial m_{jt}}$, being the revenue elasticity of material inputs.

[18] Indeed, notice that, from equation (A6), regressing just

$$s_{jt} = \log\left(\begin{array}{c} \gamma_0 + \gamma_k k_{jt} + \gamma_l l_{jt} + \gamma_m m_{jt} + \gamma_{kk} k_{jt}^2 + \gamma_{ll} l_{jt}^2 \\ + \gamma_{mm} m_{jt}^2 + \gamma_{kl} k_{jt} l_{jt} + \gamma_{km} k_{jt} m_{jt} + \gamma_{lm} l_{jt} m_{jt} \end{array}\right) - \varepsilon_{jt}$$

delivers the vector $\hat{\gamma}'$ which is an estimate for $\gamma\mathcal{E}$.

[19] $\hat{\gamma} = \hat{\gamma}' / \hat{\mathcal{E}}$.

sample variance of the estimates $\hat{\varepsilon}_{jt}$.

$$\hat{\tau}_t = \frac{1}{J(t)-1}\sum_{j(t)=1}^{J(t)}\left(\hat{\varepsilon}_{j(t)} - \frac{1}{J(t)}\sum_{j(t)=1}^{J(t)}\hat{\varepsilon}_{j(t)}\right)^2 \tag{A7}$$

Now, notice that one can invoke the Fundamental Theorem of Calculus [20] to derive the deterministic part of the revenue function from integrating the revenue elasticity of material inputs

$$\int \frac{\partial f\left(k_{jt}, l_{jt}, m_{jt}\right)}{\partial m_{jt}} dm_{jt} = f\left(k_{jt}, l_{jt}, m_{jt}\right) + \mathcal{C}\left(k_{jt}, l_{jt}\right) \tag{A8}$$

Where $\mathcal{C}\left(k_{jt}, l_{jt}\right)$ is a constant of integration. The integral has a closed form solution since a complete, second-order polynomial approximates $\frac{\partial f\left(k_{jt}, l_{jt}, m_{jt}\right)}{\partial m_{jt}}$:

$$\int \frac{\partial f\left(k_{jt}, l_{jt}, m_{jt}\right)}{\partial m_{jt}} dm_{jt} = \begin{pmatrix} \gamma_0 + \gamma_k k_{jt} + \gamma_l l_{jt} + \frac{\gamma_m}{2} m_{jt} \\ +\gamma_{kk} k_{jt}^2 + \gamma_{ll} l_{jt}^2 + \frac{\gamma_{mm}}{3} m_{jt}^2 \\ +\gamma_{kl} k_{jt} l_{jt} + \frac{\gamma_{km}}{2} k_{jt} m_{jt} + \frac{\gamma_m}{2} l_{jt} m_{jt} \end{pmatrix} m_{jt} \tag{A9}$$

Substituting the γ parameters vector with its estimate $\hat{\gamma}$ is enough to retrieve the sample analog for the integral.

Finally, consider constructing the following random variable $\mathcal{Y}_{jt}$

$$\begin{aligned} \mathcal{Y}_{jt} &\equiv y_{jt} - \varepsilon_{jt} - \int \frac{\partial f\left(k_{jt}, l_{jt}, m_{jt}\right)}{\partial m_{jt}} dm_{jt} \\ &= y_{jt} - \varepsilon_{jt} - f\left(k_{jt}, l_{jt}, m_{jt}\right) - \mathcal{C}\left(k_{jt}, l_{jt}\right) \\ &= \omega_{jt} - \mathcal{C}\left(k_{jt}, l_{jt}\right) \end{aligned} \tag{A10}$$

[20] For a more detailed discussion about the use of integration for identification, see Section IV in Gandhi, Navarro, and Rivers (2020).

Where the second line follows by equation (A8) and the third line by equations (1) and (2). Notice that revenue y_{jt} is observed. At the same time, I derived estimates in the previous steps for the ex-post productivity forecast error ε_{jt} and $\int \frac{\partial f\left(k_{jt},l_{jt},m_{jt}\right)}{\partial m_{jt}} dm_{jt}$. Then, I can compute $\mathcal{Y}_{jt}$. Call its values $\hat{\mathcal{Y}}_{jt}$.

From the last line of equation (A10), $\mathcal{Y}_{jt}$ is also a function of ω_{jt}, the persistent component of TFPR, and $\mathcal{C}(.)$, the residual function from integrating in equation (A8).

One can approximate the $\mathcal{C}(.)$ function using a second-order degree complete polynomials. Formally[21]

$$\text{(A11)} \qquad \mathcal{C}\left(k_{jt}, l_{jt}\right) = \alpha_k k_{jt} + \alpha_l l_{jt} + \alpha_{kk} k_{jt}^2 + \alpha_{ll} l_{jt}^2 + \alpha_{kl} k_{jt} l_{jt}$$

The time in-homogeneous Markovian process for ω_{jt} is given by the following truncated third-order polynomial approximation with period-specific ($1 \leq p \leq P$) coefficients

$$\text{(A12)} \qquad \omega_{jt} = m_t(\omega_{jt-1}) + \eta_{jt} = \sum_{0 \leq a \leq 3} \delta_{ap} \omega_{jt-1}^a + \eta_{jt}$$

Substituting equations (A11) and (A12) in (A10), and replacing for ω_{jt-1} using the third line of equation (A10), yields

(A13)

$$\hat{\mathcal{Y}}_{jt} = -(\alpha_k k_{jt} + \alpha_l l_{jt} + \alpha_{kk} k_{jt}^2 + \alpha_{ll} l_{jt}^2 + \alpha_{kl} k_{jt} l_{jt}) +$$
$$\sum_{0 \leq a \leq 3} \sum_{1 \leq p \leq P} I(t \in p) \delta_{ap} \left(\hat{\mathcal{Y}}_{jt-1} + \alpha_k k_{jt-1} + \alpha_l l_{jt-1} + \alpha_{kk} k_{jt-1}^2 + \alpha_{ll} l_{jt-1}^2 + \alpha_{kl} k_{jt-1} l_{jt-1}\right)^a + \eta_{jt}$$

where $I(.)$ is the indicator function.

By the allocation assumptions, k_{jt} and l_{jt} are predetermined inputs at period $t-1$. Given assumptions 3 and 4 regarding the information set available to firm j at the end of period $t-1$, their allocation is made before realizing the productivity forecast error η_{jt}.

[21] The $\mathcal{C}(.)$ function is normalized to contain no constant since this latter cannot be separately identified later from the mean productivity, $E(\omega_{jt})$.

Thus, the parameters vectors $\boldsymbol{\alpha}$, $\boldsymbol{\delta}$ and $\boldsymbol{\mu}$ can be estimated from (A13) using an exactly identified GMM system with the following unconditional moment conditions

$$
\text{(A14)} \qquad \begin{aligned} & E\left[\eta_{jt} k_{jt}^{\tau_k} l_{jt}^{\tau_l}\right] = 0 \ \forall \tau_k,\ \tau_l,\ 0 < \tau_k + \tau_l \leq 2 \\ & E\left[\eta_{jt} \hat{y}_{jt-1}^{a}\right] = 0 \ \forall a,\ 0 \leq a \leq 3,\ \forall p \end{aligned}
$$

The first set of conditions contains five moments identifying the five components of the $\boldsymbol{\alpha}$ parameter vector. The second set of moments contains $P \times 4$ conditions identifying the period-specific coefficients of the Markov process for ω_{jt}.

Then, one can estimate the cross-sectional variance of the productivity forecast error η_{jt}, σ_t, from the cross-sectional sample variance of the GMM residuals. That is

$$
\text{(A15)} \qquad \hat{\sigma}_t = \frac{1}{J(t)-1} \sum_{j(t)=1}^{J(t)} \left(\hat{\eta}_{j(t)} - \frac{1}{J(t)} \sum_{j(t)=1}^{J(t)} \hat{\eta}_{j(t)} \right)^2
$$

Having the estimates $\hat{\boldsymbol{\gamma}}$ and $\hat{\boldsymbol{\alpha}}$ for the $\boldsymbol{\gamma}$ and $\boldsymbol{\alpha}$ parameters vectors allows computing the firm-time specific revenue elasticities for material inputs, capital, and labor. Then, respectively,

(A16)

$$
\begin{aligned}
\widehat{elas}_{jt}^{M} &= \hat{\gamma}_0 + \hat{\gamma}_k k_{jt} + \hat{\gamma}_l l_{jt} + \hat{\gamma}_m m_{jt} + \hat{\gamma}_{kk} k_{jt}^2 + \hat{\gamma}_{ll} l_{jt}^2 + \hat{\gamma}_{mm} m_{jt}^2 + \hat{\gamma}_{kl} k_{jt} l_{jt} + \hat{\gamma}_{km} k_{jt} m_{jt} + \hat{\gamma}_{lm} l_{jt} m_{jt} \\
\widehat{elas}_{jt}^{K} &= m_{jt}(\hat{\gamma}_k + 2\hat{\gamma}_{kk} k_{jt} + \hat{\gamma}_{lk} l_{jt} + \frac{\hat{\gamma}_{mk}}{2} m_{jt}) - \hat{\alpha}_k - 2\hat{\alpha}_{kk} k_{jt} - \hat{\alpha}_{lk} l_{jt} \\
\widehat{elas}_{jt}^{L} &= m_{jt}(\hat{\gamma}_l + 2\hat{\gamma}_{ll} l_{jt} + \hat{\gamma}_{lk} k_{jt} + \frac{\hat{\gamma}_{ml}}{2} m_{jt}) - \hat{\alpha}_l - 2\hat{\alpha}_{ll} l_{jt} - \hat{\alpha}_{lk} k_{jt}
\end{aligned}
$$

A.1.1. Asymptotic Inference

The empirical model is consistent with the just-identified case of the two-step sieve procedure in Gandhi, Navarro, and Rivers (2020), with the difference that the polynomial parameters of the Markovian process for TFPR are period-specific in this paper. Nonetheless, the setting in this paper can also be mapped to the setting in Hahn, Liao, and Ridder (2018), ensuring not only consistency and asymptotic normality of the non-parametric estimator but also the numerical equivalence of the asymptotic variance to its parametric counterpart.

Indeed the first-stage estimator is similar to Gandhi, Navarro, and Rivers (2020) and can be expressed as

$$\hat{\gamma}_n = \arg\max_{\gamma} - \sum_{j,t} \left\{ s_{jt} - \ln \left(\sum_{r_k+r_l+r_m \leq r(n)} \gamma_{r_k,r_l,r_m} k_{jt}^{r_k} l_{jt}^{r_l} m_{jt}^{r_m} \right) \right\}^2 \tag{A17}$$

Which, using the notation in Hahn, Liao, and Ridder (2018), corresponds to

$$\hat{h}_n = \arg\max_{h \in \mathcal{H}_n} \sum_{i=1}^{n} \phi(Z_{1,i}; h) \tag{A18}$$

where $r(n)$ is a sequence growing to infinity with n, $\mathcal{H}_n$ is a sieve space with dimension increasing in n, $Z_{1,i} = \{s_{jt}, k_{jt}, l_{jt}, m_{jt}\}$, and $h = \gamma$.

On the other hand, the second-stage estimator is different from Gandhi, Navarro, and Rivers (2020) since it accounts for period-specific Markov regime variations. It can be specified as

(A19)

$$(\hat{\alpha}_n, \hat{\delta}_n) =$$

$$\arg\max_{\alpha,\delta} - \sum_{j,t} \left\{ \sum_{0<\tau_k+\tau_l \leq \tau(n)} \left[\eta_{jt}(\alpha,\delta) k_{jt}^{\tau_k} l_{jt}^{\tau_l} \right]^2 + \sum_{0<a \leq A(n)} \sum_{1 \leq p \leq P} I(t \in p) \left[\eta_{jt}(\alpha,\delta) \hat{\mathcal{Y}}_{jt-1}^{a}(\hat{\gamma}_n) \right]^2 \right\}$$

Where $\tau(n)$ and $A(n)$ are sequences growing to infinity with n, $I(.)$ is the indicator function and

$$\begin{aligned} \eta_{jt}(\alpha,\delta) = {} & \hat{\mathcal{Y}}_{jt}(\hat{\gamma}_n) + \sum_{0<\tau_k+\tau_l \leq \tau(n)} \alpha_{\tau_k,\tau_l} k_{jt}^{\tau_k} l_{jt}^{\tau_l} \\ & - \sum_{0 \leq a \leq A(n)} \sum_{1 \leq p \leq P} I(t \in p) \delta_{ap} \left(\hat{\mathcal{Y}}_{jt-1}(\hat{\gamma}_n) + \sum_{0<\tau_k+\tau_l \leq \tau(n)} \alpha_{\tau_k,\tau_l} k_{jt-1}^{\tau_k} l_{jt-1}^{\tau_l} \right)^a \end{aligned} \tag{A20}$$

The second-stage estimator corresponds, using the notation in Hahn, Liao, and Ridder (2018), to

$$\hat{g}_n = \arg\max_{g \in \mathcal{G}_n} \sum_{i=1}^{n} \psi(Z_{2,i}; g, \hat{h}_n) \tag{A21}$$

where $\mathcal{G}_n$ is a sieve space with dimension increasing in n, $g = \{\mathcal{C}(\alpha), h(\delta)\}$, and $Z_{2,i} = \{y_{jt}, k_{jt}, l_{jt}, m_{jt}, y_{jt-1}, k_{jt-1}, l_{jt-1}, m_{jt-1}\}$.

Then, similar to Gandhi, Navarro, and Rivers (2020), since I use linear polynomial sieves, under the standard assumptions in Chen (2007) and Hahn, Liao, and Ridder (2018), the estimator is consistent and asymptotically normal. Hence, I use a non-parametric bootstrap procedure to compute confidence intervals for my estimates.

It should be noted that including year fixed effects in the productivity Markov process to account for time inhomogeneities could break the consistency and asymptotic normality of the estimator. This is because the argument made in this section for ensuring those properties would no longer be valid if year fixed effects were included.

A.2. Partial Equilibrium Model Estimates

In this section, I report the results of estimating the production function for each country's industry aggregate by industry aggregate (see the industry classification in Footnote 11). The productivity Markov process $m_t(.)$ vary across four historical periods: *Begin of the millennium* (2001–2003); *Pre-crisis* (2004–2007); *Great Recession and European debt crisis* (2008–2010); *Crisis aftermath* (2011–2013); and *Post-crisis* (2014–2017). I compute standard errors via a non-parametric clustered bootstrap procedure, drawing with replacement from the pool of firms' identifiers 100 times.

TABLE A1. Food, Beverages and Tobacco

Production Function Estimates

	Germany	Spain	France	Italy	Poland	Romania
Observations	5153	156587	143753	111367	6959	26761
γ_c	0.493	0.567	0.141	0.171	0.031	0.722
	(0.050)	(0.049)	(0.083)	(0.012)	(0.045)	(0.032)
γ_k	-0.033	-0.079	-0.053	-0.082	-0.277	-0.099
	(0.012)	(0.005)	(0.031)	(0.006)	(0.013)	(0.008)
γ_l	-0.083	-0.003	0.033	0.160	0.317	0.032
	(0.021)	(0.016)	(0.019)	(0.010)	(0.026)	(0.016)
γ_m	0.148	0.135	0.041	0.043	0.075	0.164
	(0.012)	(0.012)	(0.024)	(0.004)	(0.014)	(0.011)
γ_{kk}	-0.004	-0.001	-0.000	-0.008	-0.016	0.002
	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
γ_{ll}	0.003	-0.019	-0.012	-0.046	-0.053	-0.026
	(0.003)	(0.002)	(0.007)	(0.003)	(0.003)	(0.003)
γ_{mm}	0.015	0.013	0.003	0.005	0.008	0.010
	(0.001)	(0.001)	(0.002)	(0.000)	(0.002)	(0.001)
γ_{kl}	0.003	0.007	0.015	0.012	0.059	0.010
	(0.003)	(0.001)	(0.009)	(0.001)	(0.003)	(0.002)
γ_{km}	-0.011	-0.017	-0.009	-0.003	-0.020	-0.014
	(0.003)	(0.001)	(0.005)	(0.000)	(0.002)	(0.001)
γ_{lm}	-0.011	0.011	0.001	0.018	0.015	0.002
	(0.003)	(0.003)	(0.001)	(0.001)	(0.003)	(0.002)
α_k	-0.088	-0.138	-0.551	-0.302	-0.283	0.006
	(0.086)	(0.026)	(0.065)	(0.031)	(0.200)	(0.036)
α_l	-0.323	-0.195	0.031	0.220	0.089	-0.132
	(0.093)	(0.027)	(0.051)	(0.044)	(0.247)	(0.097)
α_{kk}	-0.039	-0.022	-0.043	-0.035	-0.033	-0.022
	(0.012)	(0.002)	(0.003)	(0.004)	(0.023)	(0.003)
α_{ll}	-0.010	-0.045	-0.102	-0.155	-0.035	-0.052
	(0.014)	(0.005)	(0.007)	(0.011)	(0.039)	(0.019)
α_{kl}	-0.033	-0.036	0.075	-0.026	-0.014	-0.062
	(0.020)	(0.005)	(0.011)	(0.011)	(0.060)	(0.013)

Productivity Process Estimates

	Germany	Spain	France	Italy	Poland	Romania
2001 - 2003						
δ_1	NA	-0.184	0.026	0.058	NA	NA
	(NA)	(0.016)	(0.007)	(0.008)	(NA)	(NA)
δ_2	NA	0.540	0.927	0.802	NA	NA
	(NA)	(0.042)	(0.017)	(0.018)	(NA)	(NA)
δ_3	NA	-0.029	-0.032	-0.016	NA	NA
	(NA)	(0.028)	(0.018)	(0.010)	(NA)	(NA)
δ_4	NA	-0.002	-0.008	-0.009	NA	NA
	(NA)	(0.004)	(0.004)	(0.002)	(NA)	(NA)
2004 - 2007						
δ_1	0.074	-0.106	0.010	0.068	0.071	-0.070
	(0.037)	(0.011)	(0.009)	(0.006)	(0.222)	(0.062)
δ_2	0.758	0.636	0.920	0.860	0.826	0.973
	(0.117)	(0.030)	(0.014)	(0.016)	(0.339)	(0.140)
δ_3	-0.075	-0.042	-0.005	-0.030	0.069	0.013
	(0.255)	(0.021)	(0.020)	(0.008)	(0.227)	(0.116)
δ_4	-0.081	-0.006	-0.001	-0.008	-0.067	-0.043
	(0.148)	(0.005)	(0.004)	(0.003)	(0.065)	(0.042)
2008 - 2010						
δ_1	0.071	-0.070	0.022	0.065	0.152	-0.316
	(0.027)	(0.009)	(0.009)	(0.006)	(0.204)	(0.058)
δ_2	0.704	0.648	0.924	0.817	0.769	0.564
	(0.131)	(0.027)	(0.012)	(0.014)	(0.270)	(0.127)
δ_3	0.122	-0.062	-0.000	0.026	-0.001	-0.081
	(0.232)	(0.017)	(0.019)	(0.010)	(0.145)	(0.086)
δ_4	0.002	-0.006	0.001	-0.001	-0.005	-0.034
	(0.183)	(0.003)	(0.002)	(0.002)	(0.029)	(0.040)
2011 - 2014						
δ_1	0.063	0.005	0.037	0.077	0.244	-0.036
	(0.018)	(0.005)	(0.008)	(0.005)	(0.095)	(0.022)
δ_2	0.854	0.768	0.940	0.845	0.679	0.926
	(0.073)	(0.019)	(0.006)	(0.007)	(0.091)	(0.063)
δ_3	0.223	-0.073	0.007	0.013	0.009	0.078
	(0.149)	(0.018)	(0.017)	(0.006)	(0.059)	(0.063)
δ_4	-0.192	-0.019	0.000	-0.001	-0.007	0.001
	(0.114)	(0.005)	(0.003)	(0.001)	(0.018)	(0.025)
2015 - 2017						
δ_1	0.006	-0.095	0.016	0.051	0.220	-0.209
	(0.028)	(0.006)	(0.002)	(0.005)	(0.078)	(0.029)
δ_2	1.049	0.701	0.989	0.861	0.657	0.757
	(0.147)	(0.020)	(0.007)	(0.006)	(0.056)	(0.099)
δ_3	-0.156	-0.066	-0.042	-0.013	-0.012	0.097
	(0.180)	(0.017)	(0.010)	(0.005)	(0.032)	(0.103)
δ_4	-0.059	-0.006	-0.007	-0.003	0.006	-0.004
	(0.084)	(0.004)	(0.002)	(0.001)	(0.014)	(0.030)

TABLE A2. Textiles, Apparel and Leather

Production Function Estimates

	Germany	Spain	France	Italy	Poland	Romania
Observations	2544	98052	35389	163069	3219	26155
γ_c	0.320	0.891	0.536	0.112	0.312	0.803
	(0.093)	(0.015)	(0.029)	(0.016)	(0.032)	(0.019)
γ_k	-0.087	-0.049	-0.030	-0.051	-0.171	-0.064
	(0.029)	(0.002)	(0.002)	(0.003)	(0.014)	(0.001)
γ_l	0.082	-0.176	-0.133	0.042	0.053	-0.173
	(0.047)	(0.004)	(0.007)	(0.002)	(0.012)	(0.004)
γ_m	0.092	0.209	0.160	0.068	0.204	0.184
	(0.026)	(0.004)	(0.009)	(0.006)	(0.014)	(0.005)
γ_{kk}	-0.003	-0.001	-0.001	0.003	-0.009	-0.007
	(0.003)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
γ_{ll}	-0.022	0.009	0.011	-0.005	-0.011	0.012
	(0.006)	(0.000)	(0.001)	(0.000)	(0.002)	(0.000)
γ_{mm}	0.005	0.012	0.010	0.010	0.011	0.009
	(0.003)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
γ_{kl}	0.022	0.005	0.004	-0.001	0.025	0.006
	(0.006)	(0.000)	(0.000)	(0.000)	(0.003)	(0.000)
γ_{km}	-0.005	-0.006	-0.001	-0.010	0.000	0.003
	(0.003)	(0.000)	(0.000)	(0.000)	(0.002)	(0.001)
γ_{lm}	-0.002	-0.021	-0.016	0.008	-0.017	-0.016
	(0.006)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
α_k	-0.384	-0.033	-0.192	-0.318	-0.532	-0.351
	(0.088)	(0.007)	(0.022)	(0.020)	(0.073)	(0.034)
α_l	0.664	-0.116	-0.374	-0.157	0.194	-0.065
	(0.163)	(0.017)	(0.023)	(0.028)	(0.111)	(0.028)
α_{kk}	-0.019	-0.009	-0.003	-0.013	-0.047	-0.029
	(0.010)	(0.001)	(0.002)	(0.002)	(0.006)	(0.003)
α_{ll}	-0.166	-0.054	-0.009	0.002	-0.044	-0.033
	(0.025)	(0.004)	(0.005)	(0.004)	(0.013)	(0.005)
α_{kl}	0.092	-0.038	0.006	-0.015	0.037	0.005
	(0.021)	(0.002)	(0.004)	(0.005)	(0.013)	(0.008)

Productivity Process Estimates

	Germany	Spain	France	Italy	Poland	Romania
2001 - 2003						
δ_1	NA	-0.032	-0.012	0.121	NA	NA
	(NA)	(0.004)	(0.005)	(0.008)	(NA)	(NA)
δ_2	NA	0.747	0.698	0.874	NA	NA
	(NA)	(0.025)	(0.020)	(0.017)	(NA)	(NA)
δ_3	NA	-0.102	-0.127	-0.004	NA	NA
	(NA)	(0.038)	(0.020)	(0.010)	(NA)	(NA)
δ_4	NA	-0.054	-0.026	-0.020	NA	NA
	(NA)	(0.013)	(0.005)	(0.004)	(NA)	(NA)
2004 - 2007						
δ_1	3.276	-0.035	-0.012	0.086	0.342	-0.067
	(1.813)	(0.004)	(0.006)	(0.008)	(0.128)	(0.016)
δ_2	-5.866	0.733	0.705	0.938	0.381	0.771
	(3.131)	(0.026)	(0.024)	(0.024)	(0.230)	(0.050)
δ_3	4.677	-0.094	-0.097	-0.018	0.223	-0.005
	(1.874)	(0.029)	(0.018)	(0.012)	(0.153)	(0.044)
δ_4	-1.037	-0.034	-0.016	-0.022	0.026	-0.033
	(0.386)	(0.009)	(0.005)	(0.005)	(0.092)	(0.021)
2008 - 2010						
δ_1	1.008	-0.027	-0.017	0.083	0.132	-0.220
	(0.790)	(0.003)	(0.004)	(0.010)	(0.127)	(0.022)
δ_2	-1.130	0.716	0.774	0.896	0.863	0.391
	(1.655)	(0.018)	(0.027)	(0.012)	(0.348)	(0.032)
δ_3	1.512	-0.158	-0.099	0.000	-0.039	-0.082
	(1.192)	(0.035)	(0.020)	(0.009)	(0.335)	(0.022)
δ_4	-0.353	-0.045	-0.015	-0.019	0.043	-0.013
	(0.301)	(0.011)	(0.008)	(0.003)	(0.127)	(0.006)
2011 - 2014						
δ_1	0.823	-0.022	0.034	0.119	0.257	-0.087
	(0.264)	(0.004)	(0.004)	(0.006)	(0.106)	(0.010)
δ_2	-0.517	0.792	0.876	0.918	0.553	0.684
	(0.494)	(0.028)	(0.027)	(0.011)	(0.299)	(0.022)
δ_3	0.981	-0.064	-0.078	-0.009	0.240	-0.104
	(0.329)	(0.029)	(0.028)	(0.006)	(0.364)	(0.022)
δ_4	-0.214	-0.062	-0.035	-0.022	-0.047	-0.026
	(0.078)	(0.016)	(0.008)	(0.003)	(0.164)	(0.007)
2015 - 2017						
δ_1	0.281	-0.053	0.006	0.099	0.324	-0.072
	(0.357)	(0.004)	(0.004)	(0.008)	(0.087)	(0.012)
δ_2	0.434	0.633	0.896	0.911	0.749	0.661
	(0.649)	(0.027)	(0.028)	(0.011)	(0.158)	(0.022)
δ_3	0.361	-0.181	-0.032	-0.015	-0.048	-0.123
	(0.402)	(0.026)	(0.024)	(0.006)	(0.158)	(0.020)
δ_4	-0.075	-0.025	-0.016	-0.017	0.006	-0.026
	(0.085)	(0.010)	(0.007)	(0.003)	(0.057)	(0.005)

TABLE A3. Wood, Paper, and Printing

Production Function Estimates

	Germany	Spain	France	Italy	Poland	Romania
Observations	5997	155263	82221	109908	6075	29486
γ_c	0.123	0.572	0.456	0.124	0.416	0.627
	(0.097)	(0.048)	(0.079)	(0.006)	(0.115)	(0.035)
γ_k	-0.040	-0.105	-0.029	-0.142	-0.033	-0.109
	(0.026)	(0.004)	(0.005)	(0.007)	(0.020)	(0.004)
γ_l	0.010	0.005	-0.094	0.068	-0.037	-0.050
	(0.016)	(0.021)	(0.016)	(0.003)	(0.027)	(0.013)
γ_m	0.071	0.141	0.130	0.089	0.086	0.142
	(0.050)	(0.015)	(0.023)	(0.004)	(0.035)	(0.010)
γ_{kk}	-0.002	-0.006	0.001	-0.006	0.004	-0.008
	(0.002)	(0.000)	(0.000)	(0.000)	(0.002)	(0.001)
γ_{ll}	-0.006	-0.017	0.004	-0.006	-0.001	-0.000
	(0.004)	(0.002)	(0.001)	(0.000)	(0.003)	(0.001)
γ_{mm}	0.006	0.008	0.011	0.010	0.007	0.003
	(0.004)	(0.001)	(0.002)	(0.000)	(0.003)	(0.001)
γ_{kl}	0.006	0.023	0.002	0.020	-0.001	0.011
	(0.004)	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)
γ_{km}	-0.003	-0.008	-0.008	-0.016	-0.013	0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.004)	(0.001)
γ_{lm}	-0.006	-0.004	-0.011	0.007	0.003	-0.004
	(0.005)	(0.003)	(0.002)	(0.000)	(0.005)	(0.002)
α_k	-0.437	-0.148	-0.175	-0.580	-0.121	-0.216
	(0.089)	(0.018)	(0.043)	(0.020)	(0.077)	(0.027)
α_l	0.106	-0.084	-0.394	-0.088	-0.641	-0.030
	(0.103)	(0.022)	(0.028)	(0.028)	(0.196)	(0.026)
α_{kk}	-0.033	-0.019	-0.017	-0.055	-0.023	-0.020
	(0.006)	(0.002)	(0.003)	(0.002)	(0.006)	(0.002)
α_{ll}	-0.109	-0.065	-0.031	0.012	0.034	-0.044
	(0.015)	(0.006)	(0.004)	(0.006)	(0.025)	(0.005)
α_{kl}	0.056	-0.008	-0.014	0.044	-0.047	-0.004
	(0.019)	(0.004)	(0.008)	(0.006)	(0.018)	(0.005)

Productivity Process Estimates

	Germany	Spain	France	Italy	Poland	Romania
2001 - 2003						
δ_1	NA	-0.020	-0.086	0.213	NA	NA
	(NA)	(0.004)	(0.008)	(0.019)	(NA)	(NA)
δ_2	NA	0.719	0.747	0.717	NA	NA
	(NA)	(0.022)	(0.036)	(0.029)	(NA)	(NA)
δ_3	NA	-0.004	-0.105	0.019	NA	NA
	(NA)	(0.034)	(0.039)	(0.020)	(NA)	(NA)
δ_4	NA	-0.006	-0.030	-0.029	NA	NA
	(NA)	(0.012)	(0.009)	(0.006)	(NA)	(NA)
2004 - 2007						
δ_1	0.050	-0.002	-0.046	0.231	-0.223	-0.193
	(0.028)	(0.003)	(0.007)	(0.021)	(0.231)	(0.053)
δ_2	0.893	0.822	0.797	0.771	0.674	0.350
	(0.109)	(0.015)	(0.021)	(0.028)	(0.501)	(0.202)
δ_3	0.096	-0.026	-0.138	-0.031	-0.122	-0.364
	(0.179)	(0.044)	(0.030)	(0.012)	(0.435)	(0.194)
δ_4	-0.045	-0.025	-0.045	-0.008	-0.016	-0.050
	(0.107)	(0.011)	(0.009)	(0.004)	(0.147)	(0.045)
2008 - 2010						
δ_1	0.066	-0.014	-0.058	0.220	-0.288	-0.175
	(0.041)	(0.006)	(0.005)	(0.028)	(0.221)	(0.021)
δ_2	0.861	0.865	0.812	0.776	0.564	0.561
	(0.093)	(0.014)	(0.018)	(0.033)	(0.451)	(0.060)
δ_3	0.056	0.110	-0.091	-0.019	-0.235	-0.101
	(0.067)	(0.062)	(0.028)	(0.010)	(0.330)	(0.065)
δ_4	-0.039	0.015	-0.017	-0.019	-0.063	-0.027
	(0.028)	(0.022)	(0.010)	(0.004)	(0.095)	(0.012)
2011 - 2013						
δ_1	0.048	-0.014	-0.016	0.228	-0.327	-0.021
	(0.021)	(0.004)	(0.005)	(0.022)	(0.127)	(0.008)
δ_2	0.949	0.852	0.854	0.812	0.283	0.760
	(0.046)	(0.012)	(0.022)	(0.025)	(0.231)	(0.037)
δ_3	0.020	0.004	-0.084	-0.045	-0.445	-0.136
	(0.035)	(0.030)	(0.030)	(0.007)	(0.167)	(0.061)
δ_4	-0.025	-0.007	-0.037	-0.009	-0.084	-0.054
	(0.014)	(0.020)	(0.011)	(0.004)	(0.039)	(0.020)
2014 - 2017						
δ_1	-0.015	-0.042	-0.007	0.265	-0.124	-0.066
	(0.028)	(0.003)	(0.005)	(0.015)	(0.062)	(0.012)
δ_2	1.047	0.867	0.887	0.761	1.002	0.628
	(0.052)	(0.022)	(0.031)	(0.016)	(0.143)	(0.026)
δ_3	-0.023	-0.023	-0.139	-0.047	0.126	-0.058
	(0.036)	(0.053)	(0.035)	(0.006)	(0.106)	(0.044)
δ_4	-0.018	-0.007	-0.025	-0.011	0.008	-0.020
	(0.014)	(0.014)	(0.012)	(0.002)	(0.022)	(0.012)

TABLE A4. Coke, Chemicals, and Pharmaceuticals

Production Function Estimates

	Germany	Spain	France	Italy	Poland	Romania
Observations	5653	39794	21373	45809	2916	4797
γ_c	0.019	0.596	0.549	0.020	0.539	0.654
	(0.022)	(0.030)	(0.025)	(0.004)	(0.071)	(0.068)
γ_k	-0.084	-0.089	-0.042	-0.096	-0.146	-0.081
	(0.026)	(0.007)	(0.004)	(0.011)	(0.017)	(0.014)
γ_l	0.091	-0.060	-0.123	0.186	-0.054	-0.082
	(0.026)	(0.012)	(0.008)	(0.022)	(0.038)	(0.026)
γ_m	0.070	0.134	0.167	0.018	0.190	0.150
	(0.025)	(0.007)	(0.007)	(0.002)	(0.021)	(0.017)
γ_{kk}	-0.003	-0.003	-0.001	0.005	-0.014	-0.001
	(0.001)	(0.001)	(0.000)	(0.001)	(0.002)	(0.001)
γ_{ll}	-0.016	-0.002	0.007	-0.040	-0.001	0.000
	(0.005)	(0.002)	(0.001)	(0.005)	(0.005)	(0.002)
γ_{mm}	0.008	0.008	0.012	0.004	0.014	0.009
	(0.003)	(0.000)	(0.001)	(0.000)	(0.002)	(0.001)
γ_{kl}	0.016	0.014	0.006	0.021	0.026	0.010
	(0.005)	(0.002)	(0.001)	(0.002)	(0.004)	(0.002)
γ_{km}	-0.001	-0.008	-0.002	-0.015	-0.004	-0.009
	(0.003)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
γ_{lm}	-0.006	-0.008	-0.020	0.023	-0.018	-0.011
	(0.003)	(0.001)	(0.001)	(0.003)	(0.005)	(0.003)
α_k	-0.806	-0.144	-0.172	-0.455	-0.358	-0.113
	(0.129)	(0.022)	(0.030)	(0.046)	(0.111)	(0.045)
α_l	0.720	-0.257	-0.273	0.439	-0.322	-0.175
	(0.202)	(0.037)	(0.033)	(0.063)	(0.161)	(0.067)
α_{kk}	-0.021	-0.019	-0.007	-0.014	-0.043	-0.017
	(0.014)	(0.003)	(0.003)	(0.005)	(0.010)	(0.006)
α_{ll}	-0.178	-0.022	-0.048	-0.144	0.006	-0.041
	(0.031)	(0.010)	(0.007)	(0.010)	(0.023)	(0.012)
α_{kl}	0.140	-0.026	0.000	0.066	0.010	-0.029
	(0.035)	(0.006)	(0.008)	(0.014)	(0.025)	(0.010)

Productivity Process Estimates

	Germany	Spain	France	Italy	Poland	Romania
2001 - 2003						
δ_1	NA	0.009	0.011	0.258	NA	NA
	(NA)	(0.003)	(0.006)	(0.026)	(NA)	(NA)
δ_2	NA	0.920	0.877	0.799	NA	NA
	(NA)	(0.026)	(0.020)	(0.032)	(NA)	(NA)
δ_3	NA	0.014	-0.045	-0.012	NA	NA
	(NA)	(0.078)	(0.056)	(0.015)	(NA)	(NA)
δ_4	NA	-0.079	-0.049	-0.011	NA	NA
	(NA)	(0.042)	(0.031)	(0.004)	(NA)	(NA)
2004 - 2007						
δ_1	1.203	0.034	0.055	0.164	0.004	-0.192
	(0.402)	(0.004)	(0.008)	(0.023)	(0.032)	(0.098)
δ_2	0.324	0.926	0.836	0.933	0.892	0.338
	(0.270)	(0.016)	(0.024)	(0.025)	(0.109)	(0.314)
δ_3	0.032	0.035	-0.128	0.007	-0.074	-0.597
	(0.086)	(0.047)	(0.047)	(0.012)	(0.238)	(0.324)
δ_4	0.014	-0.047	-0.048	-0.021	-0.146	-0.198
	(0.021)	(0.040)	(0.029)	(0.004)	(0.202)	(0.106)
2008 - 2010						
δ_1	0.504	0.018	0.016	0.157	0.015	-0.229
	(0.214)	(0.003)	(0.006)	(0.030)	(0.018)	(0.065)
δ_2	0.734	0.908	0.935	0.851	0.969	0.487
	(0.263)	(0.014)	(0.028)	(0.028)	(0.073)	(0.237)
δ_3	0.002	0.049	-0.113	0.024	-0.095	-0.357
	(0.134)	(0.030)	(0.043)	(0.012)	(0.172)	(0.285)
δ_4	0.006	-0.008	-0.080	-0.008	-0.273	-0.150
	(0.023)	(0.045)	(0.029)	(0.004)	(0.140)	(0.111)
2011 - 2013						
δ_1	0.455	0.023	0.070	0.153	0.053	-0.044
	(0.241)	(0.003)	(0.008)	(0.018)	(0.038)	(0.014)
δ_2	0.753	1.002	0.933	0.902	0.810	0.882
	(0.149)	(0.017)	(0.039)	(0.017)	(0.101)	(0.056)
δ_3	0.020	-0.020	-0.120	0.030	-0.248	0.012
	(0.090)	(0.025)	(0.053)	(0.012)	(0.155)	(0.087)
δ_4	0.003	-0.136	-0.088	-0.013	-0.078	-0.019
	(0.021)	(0.036)	(0.037)	(0.004)	(0.054)	(0.049)
2014 - 2017						
δ_1	0.397	-0.051	0.004	0.095	-0.016	-0.082
	(0.182)	(0.005)	(0.007)	(0.027)	(0.026)	(0.017)
δ_2	0.735	0.855	0.911	0.925	0.877	0.874
	(0.137)	(0.016)	(0.030)	(0.025)	(0.055)	(0.067)
δ_3	0.037	-0.115	-0.061	0.029	-0.035	-0.060
	(0.088)	(0.033)	(0.052)	(0.016)	(0.077)	(0.130)
δ_4	0.000	-0.088	-0.018	-0.022	-0.058	-0.088
	(0.019)	(0.033)	(0.024)	(0.006)	(0.029)	(0.075)

TABLE A5. Rubber, Plastics, Metallic and Non-Metallic Mineral Products, Fabricated Metal Products

Production Function Estimates

	Germany	Spain	France	Italy	Poland	Romania
Observations	25363	333239	175009	431855	18733	41745
γ_c	0.187	0.858	0.584	0.542	0.361	0.339
	(0.131)	(0.018)	(0.016)	(0.029)	(0.202)	(0.072)
γ_k	-0.037	-0.058	-0.039	-0.019	-0.040	-0.151
	(0.027)	(0.001)	(0.001)	(0.001)	(0.023)	(0.032)
γ_l	-0.026	-0.152	-0.133	-0.131	-0.078	-0.030
	(0.018)	(0.008)	(0.004)	(0.007)	(0.043)	(0.006)
γ_m	0.086	0.206	0.188	0.120	0.094	0.146
	(0.061)	(0.004)	(0.005)	(0.010)	(0.056)	(0.031)
γ_{kk}	-0.002	-0.001	-0.001	0.002	-0.006	-0.009
	(0.001)	(0.000)	(0.000)	(0.000)	(0.003)	(0.002)
γ_{ll}	-0.000	0.005	0.007	0.010	0.006	0.002
	(0.001)	(0.001)	(0.000)	(0.000)	(0.003)	(0.001)
γ_{mm}	0.006	0.012	0.015	0.005	0.002	0.008
	(0.004)	(0.000)	(0.000)	(0.001)	(0.003)	(0.002)
γ_{kl}	0.007	0.006	0.006	0.004	0.004	0.023
	(0.005)	(0.000)	(0.000)	(0.000)	(0.003)	(0.005)
γ_{km}	-0.001	-0.006	-0.005	-0.004	0.006	-0.003
	(0.001)	(0.000)	(0.000)	(0.000)	(0.003)	(0.001)
γ_{lm}	-0.011	-0.018	-0.023	-0.006	-0.008	-0.012
	(0.008)	(0.001)	(0.001)	(0.002)	(0.006)	(0.003)
α_k	-0.543	-0.029	-0.221	-0.024	-0.279	-0.412
	(0.096)	(0.005)	(0.009)	(0.009)	(0.087)	(0.084)
α_l	0.176	-0.086	-0.124	-0.536	-0.669	-0.235
	(0.067)	(0.009)	(0.008)	(0.026)	(0.118)	(0.051)
α_{kk}	-0.029	-0.009	-0.016	0.009	-0.031	-0.033
	(0.005)	(0.001)	(0.001)	(0.001)	(0.006)	(0.003)
α_{ll}	-0.118	-0.065	-0.070	0.009	0.034	-0.004
	(0.014)	(0.002)	(0.002)	(0.006)	(0.014)	(0.007)
α_{kl}	0.090	-0.032	0.016	-0.031	-0.020	0.008
	(0.020)	(0.001)	(0.002)	(0.002)	(0.016)	(0.016)

Productivity Process Estimates

	Germany	Spain	France	Italy	Poland	Romania
2001 - 2003						
δ_1	NA	0.011	-0.007	-0.192	NA	NA
	(NA)	(0.002)	(0.003)	(0.009)	(NA)	(NA)
δ_2	NA	0.872	0.919	0.668	NA	NA
	(NA)	(0.014)	(0.007)	(0.018)	(NA)	(NA)
δ_3	NA	-0.017	-0.031	-0.054	NA	NA
	(NA)	(0.027)	(0.034)	(0.016)	(NA)	(NA)
δ_4	NA	-0.076	-0.014	-0.012	NA	NA
	(NA)	(0.022)	(0.009)	(0.003)	(NA)	(NA)
2004 - 2007						
δ_1	0.139	0.051	0.048	-0.097	-0.118	-0.129
	(0.013)	(0.002)	(0.003)	(0.008)	(0.055)	(0.026)
δ_2	0.865	0.928	0.903	0.690	0.985	0.640
	(0.066)	(0.005)	(0.007)	(0.015)	(0.152)	(0.092)
δ_3	0.066	-0.024	0.014	-0.073	0.111	-0.100
	(0.098)	(0.021)	(0.039)	(0.011)	(0.106)	(0.092)
δ_4	-0.015	-0.052	-0.005	-0.014	0.002	-0.032
	(0.042)	(0.012)	(0.010)	(0.003)	(0.013)	(0.016)
2008 - 2010						
δ_1	0.061	0.019	0.023	-0.144	-0.163	-0.199
	(0.017)	(0.002)	(0.002)	(0.006)	(0.048)	(0.042)
δ_2	0.888	0.929	0.925	0.673	0.936	0.521
	(0.048)	(0.010)	(0.025)	(0.013)	(0.134)	(0.026)
δ_3	0.012	-0.002	-0.058	-0.064	0.055	-0.066
	(0.036)	(0.028)	(0.044)	(0.014)	(0.089)	(0.025)
δ_4	-0.013	-0.088	-0.052	-0.018	-0.001	-0.012
	(0.016)	(0.020)	(0.018)	(0.003)	(0.011)	(0.005)
2011 - 2013						
δ_1	0.127	-0.020	0.054	-0.126	-0.073	-0.066
	(0.023)	(0.002)	(0.002)	(0.008)	(0.030)	(0.027)
δ_2	0.847	0.885	0.849	0.630	0.937	0.654
	(0.046)	(0.005)	(0.017)	(0.015)	(0.082)	(0.028)
δ_3	0.021	-0.031	0.032	-0.056	0.032	-0.082
	(0.029)	(0.016)	(0.022)	(0.009)	(0.045)	(0.022)
δ_4	-0.004	-0.040	0.005	-0.013	-0.002	-0.012
	(0.012)	(0.014)	(0.014)	(0.002)	(0.006)	(0.005)
2014 - 2017						
δ_1	-0.018	-0.055	0.010	-0.147	-0.167	-0.112
	(0.021)	(0.002)	(0.002)	(0.008)	(0.043)	(0.030)
δ_2	1.052	0.709	0.990	0.617	0.872	0.629
	(0.059)	(0.013)	(0.014)	(0.014)	(0.095)	(0.025)
δ_3	-0.030	-0.194	-0.102	-0.095	0.047	-0.056
	(0.054)	(0.043)	(0.023)	(0.009)	(0.062)	(0.021)
δ_4	-0.007	-0.066	-0.018	-0.017	0.001	-0.007
	(0.020)	(0.018)	(0.008)	(0.003)	(0.010)	(0.004)

TABLE A6. Electronic, Optical Products and Electrical Equipment Production Function Estimates

	Germany	Spain	France	Italy	Poland	Romania
Observations	10030	32404	31683	92970	3569	5705
γ_c	0.090	0.696	0.115	0.538	0.700	0.323
	(0.036)	(0.066)	(0.171)	(0.018)	(0.065)	(0.042)
γ_k	-0.058	-0.039	-0.008	-0.027	-0.116	-0.129
	(0.022)	(0.005)	(0.011)	(0.002)	(0.011)	(0.014)
γ_l	0.007	-0.103	-0.036	-0.088	-0.125	-0.023
	(0.004)	(0.023)	(0.051)	(0.003)	(0.028)	(0.007)
γ_m	0.050	0.144	0.028	0.150	0.211	0.118
	(0.019)	(0.019)	(0.043)	(0.005)	(0.020)	(0.015)
γ_{kk}	-0.005	-0.001	0.000	-0.001	-0.016	-0.006
	(0.002)	(0.000)	(0.000)	(0.000)	(0.002)	(0.001)
γ_{ll}	-0.003	0.003	0.004	0.001	0.008	-0.000
	(0.001)	(0.002)	(0.005)	(0.000)	(0.003)	(0.001)
γ_{mm}	0.003	0.006	0.002	0.010	0.006	0.008
	(0.001)	(0.002)	(0.003)	(0.000)	(0.002)	(0.001)
γ_{kl}	0.012	0.006	-0.000	0.002	0.014	0.015
	(0.004)	(0.001)	(0.000)	(0.000)	(0.002)	(0.002)
γ_{km}	-0.000	-0.001	-0.002	-0.002	0.011	-0.008
	(0.000)	(0.001)	(0.003)	(0.000)	(0.003)	(0.001)
γ_{lm}	-0.005	-0.008	-0.003	-0.013	-0.017	-0.006
	(0.002)	(0.004)	(0.005)	(0.000)	(0.004)	(0.001)
α_k	-0.503	-0.061	-0.329	-0.039	-0.190	-0.486
	(0.108)	(0.021)	(0.078)	(0.014)	(0.077)	(0.072)
α_l	-0.537	-0.147	-0.670	-0.292	-0.519	-0.275
	(0.139)	(0.027)	(0.053)	(0.013)	(0.106)	(0.092)
α_{kk}	-0.056	-0.004	-0.021	-0.001	-0.030	-0.046
	(0.009)	(0.002)	(0.005)	(0.002)	(0.010)	(0.007)
α_{ll}	-0.018	-0.057	0.006	-0.042	0.027	-0.004
	(0.017)	(0.006)	(0.013)	(0.003)	(0.015)	(0.012)
α_{kl}	0.077	-0.004	-0.001	-0.031	-0.022	-0.001
	(0.024)	(0.008)	(0.019)	(0.003)	(0.017)	(0.015)

Productivity Process Estimates

	Germany	Spain	France	Italy	Poland	Romania
2001 - 2003						
δ_1	NA	0.046	-0.088	-0.034	NA	NA
	(NA)	(0.011)	(0.011)	(0.004)	(NA)	(NA)
δ_2	NA	0.908	0.831	0.731	NA	NA
	(NA)	(0.021)	(0.031)	(0.019)	(NA)	(NA)
δ_3	NA	-0.131	-0.122	-0.147	NA	NA
	(NA)	(0.041)	(0.033)	(0.040)	(NA)	(NA)
δ_4	NA	-0.051	-0.042	-0.030	NA	NA
	(NA)	(0.024)	(0.011)	(0.009)	(NA)	(NA)
2004 - 2007						
δ_1	-0.017	0.030	-0.037	-0.005	-0.167	-0.026
	(0.037)	(0.007)	(0.012)	(0.003)	(0.083)	(0.049)
δ_2	0.774	0.939	0.816	0.769	0.484	0.592
	(0.049)	(0.024)	(0.047)	(0.019)	(0.280)	(0.140)
δ_3	-0.072	-0.026	-0.104	-0.107	-0.346	-0.349
	(0.042)	(0.030)	(0.044)	(0.026)	(0.441)	(0.202)
δ_4	-0.013	-0.039	-0.029	-0.030	-0.074	-0.142
	(0.017)	(0.042)	(0.010)	(0.006)	(0.290)	(0.094)
2008 - 2010						
δ_1	-0.068	-0.005	-0.041	-0.042	-0.197	-0.030
	(0.028)	(0.006)	(0.007)	(0.003)	(0.073)	(0.061)
δ_2	0.841	0.929	0.934	0.782	0.774	0.474
	(0.031)	(0.022)	(0.034)	(0.012)	(0.218)	(0.059)
δ_3	-0.043	0.043	-0.016	-0.093	0.150	-0.099
	(0.023)	(0.033)	(0.042)	(0.022)	(0.238)	(0.059)
δ_4	-0.002	-0.063	-0.007	-0.031	0.011	-0.020
	(0.005)	(0.042)	(0.010)	(0.006)	(0.075)	(0.016)
2011 - 2013						
δ_1	-0.010	0.022	-0.017	-0.021	-0.151	-0.024
	(0.030)	(0.007)	(0.006)	(0.003)	(0.055)	(0.031)
δ_2	0.848	0.918	0.930	0.752	0.584	0.784
	(0.028)	(0.024)	(0.030)	(0.014)	(0.111)	(0.051)
δ_3	-0.019	-0.124	-0.006	-0.138	-0.212	-0.115
	(0.023)	(0.052)	(0.040)	(0.022)	(0.120)	(0.044)
δ_4	-0.005	-0.042	-0.004	-0.031	-0.045	-0.032
	(0.003)	(0.043)	(0.016)	(0.006)	(0.054)	(0.014)
2014 - 2017						
δ_1	0.007	-0.121	-0.016	-0.028	-0.187	-0.029
	(0.014)	(0.011)	(0.010)	(0.003)	(0.060)	(0.044)
δ_2	0.936	0.703	0.953	0.736	0.671	0.642
	(0.019)	(0.022)	(0.050)	(0.017)	(0.106)	(0.036)
δ_3	-0.024	-0.046	-0.023	-0.142	-0.030	-0.061
	(0.018)	(0.049)	(0.063)	(0.027)	(0.096)	(0.043)
δ_4	-0.002	-0.002	-0.012	-0.028	-0.008	0.000
	(0.002)	(0.033)	(0.017)	(0.007)	(0.028)	(0.008)

TABLE A7. Machinery, Motor Vehicles and Other Transport Equipment Production Function Estimates

	Germany	Spain	France	Italy	Poland	Romania
Observations	16757	82156	53558	190767	7151	9115
γ_c	0.362	0.850	0.245	0.222	0.420	0.133
	(0.067)	(0.016)	(0.025)	(0.007)	(0.041)	(0.038)
γ_k	-0.046	-0.045	-0.095	-0.133	-0.111	-0.075
	(0.010)	(0.003)	(0.008)	(0.004)	(0.011)	(0.005)
γ_l	-0.056	-0.131	-0.000	-0.030	0.031	0.072
	(0.015)	(0.007)	(0.006)	(0.001)	(0.016)	(0.012)
γ_m	0.146	0.208	0.124	0.116	0.167	0.028
	(0.026)	(0.004)	(0.010)	(0.004)	(0.011)	(0.013)
γ_{kk}	-0.004	-0.001	-0.004	-0.005	-0.005	-0.000
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
γ_{ll}	-0.001	-0.001	-0.008	0.008	-0.013	-0.010
	(0.002)	(0.001)	(0.001)	(0.000)	(0.002)	(0.001)
γ_{mm}	0.007	0.013	0.014	0.010	0.010	0.001
	(0.002)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)
γ_{kl}	0.008	0.007	0.014	0.026	0.020	0.011
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
γ_{km}	0.004	-0.005	-0.011	-0.006	-0.004	-0.008
	(0.002)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)
γ_{lm}	-0.019	-0.018	-0.006	-0.007	-0.012	0.007
	(0.003)	(0.001)	(0.001)	(0.000)	(0.002)	(0.002)
α_k	-0.251	-0.028	-0.398	-0.425	-0.272	-0.741
	(0.078)	(0.014)	(0.034)	(0.022)	(0.067)	(0.088)
α_l	-0.018	-0.021	-0.251	-0.455	0.271	0.280
	(0.109)	(0.013)	(0.032)	(0.020)	(0.085)	(0.096)
α_{kk}	-0.020	-0.005	-0.036	-0.021	-0.018	-0.053
	(0.008)	(0.002)	(0.004)	(0.002)	(0.007)	(0.007)
α_{ll}	-0.097	-0.081	-0.036	0.058	-0.087	-0.075
	(0.020)	(0.003)	(0.006)	(0.005)	(0.012)	(0.011)
α_{kl}	0.040	-0.017	0.013	0.045	0.030	0.091
	(0.022)	(0.003)	(0.008)	(0.006)	(0.017)	(0.017)

Productivity Process Estimates

	Germany	Spain	France	Italy	Poland	Romania
2001 - 2003						
δ_1	NA	0.010	0.097	0.110	NA	NA
	(NA)	(0.003)	(0.013)	(0.010)	(NA)	(NA)
δ_2	NA	0.735	0.714	0.700	NA	NA
	(NA)	(0.027)	(0.028)	(0.015)	(NA)	(NA)
δ_3	NA	0.017	-0.081	-0.017	NA	NA
	(NA)	(0.058)	(0.017)	(0.010)	(NA)	(NA)
δ_4	NA	0.001	-0.012	-0.002	NA	NA
	(NA)	(0.015)	(0.003)	(0.002)	(NA)	(NA)
2004 - 2007						
δ_1	0.070	0.034	0.089	0.131	0.182	0.143
	(0.009)	(0.004)	(0.013)	(0.007)	(0.042)	(0.022)
δ_2	0.897	0.793	0.797	0.808	0.762	0.839
	(0.031)	(0.018)	(0.028)	(0.013)	(0.161)	(0.027)
δ_3	0.004	-0.045	-0.060	-0.064	0.014	0.060
	(0.047)	(0.054)	(0.020)	(0.008)	(0.193)	(0.045)
δ_4	-0.002	-0.025	-0.014	-0.009	-0.051	-0.010
	(0.020)	(0.013)	(0.006)	(0.002)	(0.107)	(0.033)
2008 - 2010						
δ_1	0.058	0.034	0.116	0.129	0.050	0.194
	(0.014)	(0.004)	(0.017)	(0.012)	(0.033)	(0.042)
δ_2	0.870	0.840	0.729	0.757	0.840	0.690
	(0.050)	(0.016)	(0.034)	(0.016)	(0.124)	(0.032)
δ_3	-0.030	-0.171	-0.064	-0.043	0.268	-0.003
	(0.060)	(0.048)	(0.020)	(0.006)	(0.220)	(0.036)
δ_4	-0.037	-0.043	-0.004	-0.008	-0.202	-0.032
	(0.023)	(0.018)	(0.006)	(0.002)	(0.169)	(0.016)
2011 - 2013						
δ_1	0.070	0.029	0.127	0.151	0.051	0.102
	(0.019)	(0.004)	(0.013)	(0.009)	(0.023)	(0.020)
δ_2	0.771	0.886	0.742	0.760	1.026	0.892
	(0.043)	(0.016)	(0.032)	(0.010)	(0.072)	(0.027)
δ_3	0.091	-0.141	-0.052	-0.056	-0.032	0.035
	(0.040)	(0.043)	(0.015)	(0.005)	(0.058)	(0.026)
δ_4	0.000	-0.070	-0.003	-0.005	-0.083	-0.034
	(0.013)	(0.037)	(0.005)	(0.001)	(0.046)	(0.011)
2014 - 2017						
δ_1	0.009	-0.037	0.118	0.136	0.099	0.110
	(0.019)	(0.006)	(0.020)	(0.009)	(0.038)	(0.021)
δ_2	0.991	0.662	0.764	0.783	1.028	0.841
	(0.059)	(0.014)	(0.044)	(0.010)	(0.125)	(0.022)
δ_3	-0.005	-0.171	-0.069	-0.065	-0.109	0.039
	(0.049)	(0.037)	(0.024)	(0.005)	(0.079)	(0.025)
δ_4	-0.023	-0.048	-0.008	-0.006	-0.098	-0.029
	(0.016)	(0.017)	(0.008)	(0.001)	(0.042)	(0.007)

TABLE A8. Furniture and Other Manufacturing

Production Function Estimates

	Germany	Spain	France	Italy	Poland	Romania
Observations	4906	102639	63528	116022	6959	24629
γ_c	0.395	1.177	0.596	0.570	0.339	1.018
	(0.076)	(0.015)	(0.024)	(0.018)	(0.029)	(0.032)
γ_k	-0.061	0.021	-0.048	-0.059	-0.157	-0.137
	(0.012)	(0.006)	(0.002)	(0.003)	(0.009)	(0.012)
γ_l	-0.071	-0.268	-0.130	-0.139	-0.034	-0.175
	(0.022)	(0.006)	(0.005)	(0.005)	(0.010)	(0.010)
γ_m	0.147	0.231	0.176	0.170	0.154	0.289
	(0.025)	(0.004)	(0.007)	(0.006)	(0.010)	(0.011)
γ_{kk}	-0.004	0.003	-0.006	-0.001	-0.013	-0.006
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
γ_{ll}	0.002	0.013	0.006	0.012	0.001	0.006
	(0.002)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
γ_{mm}	0.011	0.012	0.012	0.013	0.014	0.015
	(0.002)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
γ_{kl}	0.009	-0.007	0.004	0.003	0.019	0.026
	(0.002)	(0.001)	(0.000)	(0.000)	(0.001)	(0.003)
γ_{km}	-0.002	-0.004	-0.003	-0.007	-0.004	-0.006
	(0.002)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
γ_{lm}	-0.017	-0.026	-0.020	-0.013	-0.005	-0.033
	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
α_k	-0.416	0.044	-0.241	-0.108	-0.553	0.076
	(0.064)	(0.005)	(0.016)	(0.009)	(0.062)	(0.034)
α_l	0.035	0.091	-0.140	-0.463	-0.168	0.221
	(0.089)	(0.012)	(0.022)	(0.019)	(0.048)	(0.057)
α_{kk}	-0.036	0.001	-0.036	-0.010	-0.052	-0.000
	(0.007)	(0.001)	(0.002)	(0.001)	(0.007)	(0.003)
α_{ll}	-0.082	-0.109	-0.083	0.008	0.001	-0.091
	(0.013)	(0.003)	(0.004)	(0.004)	(0.007)	(0.009)
α_{kl}	0.049	-0.033	0.003	-0.042	0.035	-0.037
	(0.015)	(0.002)	(0.005)	(0.003)	(0.012)	(0.008)

Productivity Process Estimates

	Germany	Spain	France	Italy	Poland	Romania
2001 - 2003						
δ_1	NA	-0.020	-0.067	-0.066	NA	NA
	(NA)	(0.002)	(0.008)	(0.006)	(NA)	(NA)
δ_2	NA	0.768	0.648	0.675	NA	NA
	(NA)	(0.024)	(0.022)	(0.033)	(NA)	(NA)
δ_3	NA	-0.005	-0.121	-0.120	NA	NA
	(NA)	(0.059)	(0.022)	(0.043)	(NA)	(NA)
δ_4	NA	-0.058	-0.026	-0.044	NA	NA
	(NA)	(0.030)	(0.006)	(0.014)	(NA)	(NA)
2004 - 2007						
δ_1	0.210	0.004	-0.053	-0.036	0.128	-0.035
	(0.069)	(0.002)	(0.008)	(0.005)	(0.046)	(0.047)
δ_2	0.324	0.777	0.677	0.752	0.848	0.776
	(0.317)	(0.025)	(0.021)	(0.025)	(0.138)	(0.158)
δ_3	0.811	-0.036	-0.133	-0.055	-0.035	-0.100
	(0.594)	(0.052)	(0.020)	(0.031)	(0.150)	(0.173)
δ_4	-0.362	-0.070	-0.027	-0.023	-0.059	-0.058
	(0.403)	(0.036)	(0.005)	(0.009)	(0.088)	(0.064)
2008 - 2010						
δ_1	0.091	0.013	-0.027	-0.040	0.303	-0.005
	(0.026)	(0.003)	(0.006)	(0.004)	(0.070)	(0.025)
δ_2	0.716	0.817	0.765	0.754	0.511	0.512
	(0.099)	(0.014)	(0.019)	(0.024)	(0.118)	(0.068)
δ_3	0.136	-0.095	-0.104	-0.045	0.009	-0.114
	(0.098)	(0.060)	(0.022)	(0.038)	(0.078)	(0.070)
δ_4	0.036	-0.071	-0.027	-0.027	0.005	-0.037
	(0.071)	(0.025)	(0.009)	(0.013)	(0.042)	(0.028)
2011 - 2013						
δ_1	0.073	0.006	-0.022	-0.035	0.202	-0.154
	(0.015)	(0.003)	(0.007)	(0.006)	(0.042)	(0.028)
δ_2	0.989	0.793	0.752	0.683	0.820	0.385
	(0.057)	(0.017)	(0.027)	(0.018)	(0.067)	(0.060)
δ_3	-0.075	-0.022	-0.081	-0.105	-0.170	-0.112
	(0.055)	(0.042)	(0.027)	(0.022)	(0.052)	(0.077)
δ_4	-0.036	-0.058	-0.033	-0.025	-0.050	-0.005
	(0.023)	(0.024)	(0.012)	(0.006)	(0.018)	(0.023)
2014 - 2017						
δ_1	0.066	-0.055	-0.026	-0.045	0.199	-0.111
	(0.034)	(0.003)	(0.006)	(0.006)	(0.026)	(0.028)
δ_2	1.007	0.643	0.751	0.660	0.709	0.426
	(0.128)	(0.012)	(0.021)	(0.014)	(0.039)	(0.056)
δ_3	-0.081	-0.155	-0.101	-0.117	-0.052	-0.090
	(0.156)	(0.032)	(0.015)	(0.017)	(0.025)	(0.065)
δ_4	-0.026	-0.052	-0.017	-0.022	-0.004	-0.005
	(0.089)	(0.017)	(0.004)	(0.004)	(0.011)	(0.016)