Do Productivity Shocks Cause Inputs Misallocation?

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Firms exhibit varying productivity levels even within narrowly defined industries and face uncertainty when predicting future performance. This paper investigates the link between productivity uncertainty, heterogeneity, and misallocation across all inputs. Using a model where heterogeneous firms face staggered productivity shocks, creating gaps between expected and actual productivity, I find a positive association between marginal revenue product dispersions and productivity variability. The analysis reveals that productivity shocks predominantly drive marginal revenue product dispersions. By comparing baseline estimates with those from the factor shares approach, I highlight the limitations of the latter method in analyzing the effects of productivity evolution.

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1. Introduction

Firm productivity significantly influences executive decision-making regarding operations and investments. Anticipation of high productivity often leads to increased procurement of manufacturing inputs, expansion of workforce and facilities, and enhanced allocation of resources to research and development initiatives. Conversely, projections of lower productivity typically result in more conservative strategies aimed at cost reduction and profitability maintenance.

It is well-established that productivity levels vary considerably among firms, even within narrowly defined industries. Moreover, firms face dynamic uncertainty when forecasting future productivity. Productivity shocks occur unpredictably over time, causing initial forecasts to often diverge from actual productivity levels. These discrepancies between anticipated and realized productivity lead to significant divergences in input decisions, resulting in ex post misallocation despite ex ante optimal choices.

This study examines the interplay between productivity uncertainty, firm heterogeneity, and the misallocation of production inputs. I investigate the sensitivity of input allocation to cross-firm productivity differentials, which can lead to misallocation through distortions correlated with productivity levels[1]. Furthermore, I analyze the effects of productivity shocks occurring at various stages of firms' input decision processes. These shocks generate temporal fluctuations in firm-level productivity, creating discrepancies between ex ante and ex post optimal input allocations.

Consistent with established methods, this analysis uses the dispersion

[1] Examples of such distortions include financial frictions and firing costs (Bento and Restuccia 2021).

of marginal revenue product (MRP) across firms to quantify ex post misallocation (Restuccia and Rogerson (2008), Hsieh and Klenow (2009)). Under certain assumptions, significant dispersion indicates frictions preventing resources from moving to more efficient uses within an industry[2]. Asker, Collard-Wexler, and De Loecker (2014) demonstrate that for capital, a dynamic input with adjustment costs, MRP dispersion arises from productivity uncertainty, heterogeneity, and adjustment frictions[3]. My work expands on this and on David, Hopenhayn, and Venkateswaran (2016) by considering imperfect information affecting all inputs and firms at various stages. Additionally, I distinguish between cross-firm productivity variation and period-to-period changes in firm-level productivity, as suggested by David and Venkateswaran (2019) and Bento and Restuccia (2021).

This paper develops a theoretical model building on the work of Gandhi, Navarro, and Rivers (2020) (hereafter GNR) to analyze input misallocation and productivity dynamics within a production function framework. I estimate the model using a comprehensive firm-level panel dataset spanning 2000–2017 across European economies, incorporating time-varying revenue total factor productivity (TFPR) processes to capture structural shifts induced by the Global Financial Crisis. In my specification, capital and la-

[2] Misallocative factors 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)), suboptimal firm selection (Yang (2021)), factor adjustment costs, and productivity information frictions (Asker, Collard-Wexler, and De Loecker (2014), David and Venkateswaran (2019)). Other factors are 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)).

[3] Asker, Collard-Wexler, and De Loecker (2014) argue that MRP dispersion and optimal allocations can coexist, challenging the static view of suboptimality and misallocation due to capital MRP dispersion. This suggests considering adjustment costs as a fundamental economic primitive rather than purely a misallocative factor.

bor are treated as predetermined inputs, while materials are modeled as static inputs. The framework accounts for various market distortions, with productivity uncertainty serving as the sole explicitly modeled friction[4]. A key innovation of the model is its treatment of heterogeneous firms facing productivity shocks both before and after the allocation of materials. To my knowledge, this study presents the first disaggregation of productivity shocks by timing, analyzing their distinct effects on input misallocation across all production factors. I then benchmark the results against those derived using the factor share (FS) method, a widely employed technique in the productivity and misallocation literature (De Loecker and Syverson 2021).

First, I examine the relationship between MRP dispersion and TFPR variability, revealing a positive association for all inputs. This relationship is stronger for labor and materials than for capital. Regression analysis shows that the FS method generally underestimates the elasticity of MRP dispersion with respect to TFPR variance for labor and overestimates it for materials. In contrast, the FS method exhibits only a minor bias in estimating this elasticity for the capital input.

Second, I decompose TFPR into observed and shock components, assessing their respective associations with MRP dispersion. The baseline-GNR results show that productivity shocks primarily drive MRP dispersion for all inputs, while the FS approach overemphasizes the role of past productivity heterogeneity. These findings highlight the importance of accounting for rich productivity dynamics to understand productivity dispersion and its impact on input misallocation across all production inputs.

[4]This approach implicitly accounts for well-documented post-2000 European labor market rigidities, without explicitly modeling these frictions.

Additionally, I compare production function estimates derived from the GNR framework and the FS approach. My analysis reveals significant discrepancies between the two methodologies. The FS approach tends to overestimate the dispersion and average revenue elasticity of capital and materials while underestimating these statistics for labor. Furthermore, it consistently yields higher estimates for both the aggregate mean and variance of TFPR over time compared to the GNR approach. Interestingly, while the FS method produces aggregate capital MRP dispersion estimates that closely align with those of the GNR approach, it substantially underestimates the aggregate MRP dispersion for labor and materials—by approximately 20% and 30%, respectively—throughout the sample period.

Overall, my results demonstrate that productivity heterogeneity and uncertainty are linked to misallocation across countries for all inputs of the production function. There is no conceptual reason to consider capital as a special input uniquely subject to these forces. The allocation efficiency of all production inputs may depend on firm-specific production characteristics and period-to-period changes in productivity, and therefore, their revenue product dispersion should be associated with TFPR dispersion.

Furthermore, the baseline estimates show that productivity shocks drive the bulk of the dispersion and have the strongest association with input misallocation, implying that productivity uncertainty impacts misallocation more than productivity heterogeneity. This finding contrasts with conclusions drawn using the FS approach. While some uncertainty is unavoidable, policies and strategies[5] can help mitigate the uncertainties firms face. Failing to

[5] 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)).

account for their impact on input misallocation could lead to misattributing these effects to other distortions and proposing misguided policy prescriptions.

Finally, this paper highlights a cautionary tale regarding the use of the FS approach for estimating the production function. The FS approach is valued for its simplicity and flexibility, as it does not depend on a specific production function but rather on behavioral assumptions about firms, allowing for easy accommodation of extensions such as multiproduct production. However, this method relies on strict assumptions about the timing of productivity realization and input allocation, making models with richer dynamics perhaps better suited for analyzing productivity evolution and its effects.

The remainder of this paper is structured as follows. Section 2 presents the baseline theoretical framework. Section 3 describes the data used and provides relevant descriptive statistics. Section 4 outlines the empirical framework for both the baseline-GNR and FS approaches. Section 5 presents the main results, beginning with stylized facts about the production technology estimates. It then examines the sensitivity of inputs' MRP dispersion to TFPR variation and concludes with an analysis using TFPR decompositions. Finally, Section 6 discusses the limitations of the study and offers suggestions for future research.

2. Theoretical Framework

The theoretical framework builds upon GNR, augmenting it with time-varying productivity processes. This model introduces imperfect information about productivity as the primary friction, explicitly capturing the evolution of firms' uncertainty regarding their efficiency levels. It also considers heterogeneity in firms' past productivity. At the start of each production period, firms possess a specific productivity level and subsequently encounter multiple productivity shocks, occurring both before and after input allocation.

The model adopts an agnostic stance on the allocation of capital and labor, assuming only that firms predetermine these inputs relative to materials. This flexibility allows the framework to capture dynamics consistent with various distortions affecting capital and labor inputs in both static and intertemporal contexts[6]. While the framework primarily focuses on productivity uncertainty as the explicit source of friction, it remains applicable across diverse economic scenarios.

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

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

Here, ν_{jt} represents TFPR, which comprises a persistent component and an unexpected component (Olley and Pakes 1996):

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

The term ω_{jt} denotes a persistent productivity factor that firm j perfectly observes at the beginning of period t but remains unknown at time $t-1$.

[6] Distortions may include resale losses due to transaction costs, the market for lemons phenomenon (Akerlof 1970), physical costs of resale and refitting for capital, and hiring, firing, and training expenses for workers (Bloom 2009). Additionally, the model may incorporate working capital and borrowing constraints, government regulations, transportation costs, subsidies, and taxes (Hsieh and Klenow 2009).

Conversely, ε_{jt} represents a residual, short-term idiosyncratic revenue fluctuation that is observed only at the end of the period[7].

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

ASSUMPTION 1 (Persistent Productivity Process). *ω_{jt} follows a time-varying stochastic Markov process with a mean zero forecast error that realizes in period t. Specifically,*

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

where $m_t(\cdot)$ 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. Let its cross-sectional variance be time-variant, denoted as σ_t.

ASSUMPTION 2 (Productivity Shocks Realization Timing). *The forecast error η_{jt} realizes at the beginning of period t, making the persistent productivity component, ω_{jt}, known at the start of period t. In contrast, the unexpected component,*

[7] An alternative, observationally equivalent interpretation of ε_{jt} is ex-post measurement error in output. However, in this paper, I adhere to the interpretation of ε_{jt} as a productivity forecast error, following GNR. Additionally, in line with the convention in the production function estimation literature (Blum et al. 2024), I assume no measurement errors in the input variables. Recent studies examining measurement errors in capital input include Collard-Wexler and De Loecker (2016) and il Kim, Petrin, and Song (2016).

ε_{jt}, is an idiosyncratic, mean-independent, short-term output fluctuation that realizes towards the end of period t. Specifically,

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

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

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

ASSUMPTION 3 (Input Allocations). *Firm j allocates the capital and labor inputs, K_{jt} and L_{jt}, just before the start of period t. Consequently, these inputs are predetermined. In contrast, the firm allocates intermediate materials, M_{jt}, after observing ω_{jt} but before the realization of ε_{jt}, by solving a static value-added maximization problem. Thus, intermediate materials are considered a flexible production input.*

ASSUMPTION 4 (Pricing Behavior). *Firms act as price takers in both output and input markets, facing nominal input prices denoted as P^L_{jt} for wages, P^K_{jt} for the rental rate of capital, and P^M_{jt} for the unit cost of materials. The evolution of output and input prices follows a time-varying Markov process, which I do not further specify[8]. Firms pay input prices simultaneously with each input allocation.*

In other words, Assumption 4 allows for heterogeneity in input and output prices, which may be influenced by TFPR and its components, as well as

[8] A similar assumption for input prices is present in Doraszelski and Jaumandreu (2018).

by aggregate price levels, while maintaining the assumption of firms' price-taking behavior. Without loss of generality, I characterize input prices as exogenous functions of the firm's information sets as follows:

$$P_{jt}^{X} = P_{t}^{X}\left(\tilde{\mathfrak{I}}_{jt-1}\right) \quad \forall X \in \{L, K\} \tag{5}$$

$$P_{jt}^{M} = P_{t}^{M}\left(\mathfrak{I}_{jt}\right) \tag{6}$$

The timeline of events and decisions for firm j unfolds as follows.

a. At the end of period $t-1$, firm j knows the TFPR for that period, denoted as ν_{jt-1}, and the observed revenue Y_{jt-1}. This information comprises the firm's information set, $\tilde{\mathfrak{I}}_{jt-1}$.

b. Using this information, the firm makes strategic choices for the upcoming period t. Specifically, it determines the quantities of labor L_{jt} and capital K_{jt} to employ, given the nominal wage rate P_{jt}^{L} and the rental rate of capital P_{jt}^{K}. These decisions rely on the information set $\tilde{\mathfrak{I}}_{jt-1}$.

c. As period t commences, the firm experiences a realization of the productivity shock η_{jt}. With this new information, the firm updates its expectation of the period's TFPR (i.e., the firm knows ω_{jt}) and forms a new information set, $\mathfrak{I}_{jt}$.

d. Next, the firm decides on the materials allocation M_{jt} for the period, taking into account the unit price of materials P_{jt}^{M}. This decision aims to maximize value-added, solving the following optimization problem conditional on the information set $\mathfrak{I}_{jt}$:

$$\max_{M_{jt}} \left[E(F(k_{jt}, l_{jt}, m_{jt})e^{\nu_{jt}} \mid \mathfrak{I}_{jt}) - P_{jt}^{M} M_{jt}\right] \tag{7}$$

e. Just before the end of period t, the firm observes the realized shock ε_{jt}.

Consequently, it determines the period's TFPR ν_{jt} and observed revenue Y_{jt}. This updated knowledge forms the new information set $\tilde{\mathfrak{I}}_{jt}$.

Throughout this paper, I 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 illustrate how period-to-period fluctuations in firm-level productivity and cross-firm differences in historical productivity levels contribute to the dispersion of input marginal revenue products across firms within an industry, a standard measure of misallocation.

The MRP of input X is the derivative of revenue Y with respect to the allocation of input X. By applying the chain rule in calculus, one can decompose the MRP of any input X as a function of the final revenue Y_{jt}, the input allocation X_{jt}, and the revenue elasticity of that input $\frac{\partial y_{jt}}{\partial x_{jt}}$:

$$MRP^X_{jt} = \frac{\partial Y_{jt}}{\partial X_{jt}} = \frac{\partial Y_{jt}}{\partial y_{jt}}\frac{\partial y_{jt}}{\partial x_{jt}}\frac{\partial x_{jt}}{\partial X_{jt}} = \frac{Y_{jt}}{X_{jt}}\text{elas}^X_{jt} \quad \forall X \in \{K, L, M\} \tag{8}$$

Taking the natural logarithm and totally differentiating[9] with respect to TFPR leads to:

$$\frac{dmrp^X_{jt}}{d\nu_{jt}} = \frac{dy_{jt}}{d\nu_{jt}} - \frac{dx_{jt}}{d\nu_{jt}} + \frac{d\log \text{elas}^X_{jt}}{d\nu_{jt}} \tag{9}$$

[9]Note that:

$$\frac{\partial mrp^X_{jt}}{\partial y_{jt}} = -\frac{\partial mrp^X_{jt}}{\partial x_{jt}} = \frac{\partial mrp^X_{jt}}{\partial \log \text{elas}^X_{jt}} = 1$$

Equation (9) indicates that three factors determine the elasticity of an input's MRP with respect to a hypothetical variation in the firm's TFPR. The first term represents the elasticity of revenue to TFPR. The second term captures the elasticity of input allocation to TFPR. The third term accounts for the effect of changes in TFPR on the input's revenue elasticity.

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

$$\nu_{jt} = m_t(\omega_{jt-1}) + \eta_{jt} + \varepsilon_{jt} \tag{10}$$

Then, using the chain and the inverse-function rules[10], the total effect of a change in TFPR on the MRP of an input can be expressed as the combination

[10] Indeed,

$$\frac{dmrp^X_{jt}}{d\nu_{jt}} = \left(\frac{d\nu_{jt}}{dmrp^X_{jt}}\right)^{-1} = \left(\frac{dm_t(\omega_{jt-1})}{dmrp^X_{jt}} + \frac{d\eta_{jt}}{dmrp^X_{jt}} + \frac{d\varepsilon_{jt}}{dmrp^X_{jt}}\right)^{-1}$$
$$= \left(\left(\frac{\S mrp^X_{jt}}{\S\omega_{jt-1}}\left(\frac{\partial m_t(\omega_{jt-1})}{\partial\omega_{jt-1}}\right)^{-1}\right)^{-1} + \left(\frac{\S mrp^X_{jt}}{\S\eta_{jt}}\right)^{-1} + \left(\frac{\S mrp^X_{jt}}{\S\varepsilon_{jt}}\right)^{-1}\right)^{-1}$$

The symbol § refers to a *partial total derivative*. For more details, see Wainwright and Chiang (2005), page 192. In this setup, $\frac{\S mrp^X}{\S\theta}$ represents a total derivative keeping the other exogenous variables fixed. For example,

$$\frac{\S mrp^X_{jt}}{\S\omega_{jt-1}} = \left.\frac{dmrp^X_{jt}}{d\omega_{jt-1}}\right|_{d\eta_{jt}=0,d\varepsilon_{jt}=0}$$

However, since $\omega_{jt-1} \perp \eta_{jt} \perp \varepsilon_{jt}$ by Assumptions 1 and 2, I can simplify the notation by replacing the partial total derivatives with simple total derivatives:

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

of the effects of the changes in each component of TFPR on that input's MRP. More formally:

$$\frac{dmrp_{jt}^X}{d\nu_{jt}} = c\left(\frac{dmrp_{jt}^X}{d\omega_{jt-1}}, \frac{dmrp_{jt}^X}{d\eta_{jt}}, \frac{dmrp_{jt}^X}{d\varepsilon_{jt}}\right) \tag{11}$$

In turn, each productivity component effect can be decomposed as follows:

$$\frac{dmrp_{jt}^X}{d\theta} = \frac{dy_{jt}}{d\theta} - \frac{dx_{jt}}{d\theta} + \frac{d\log \text{elas}_{jt}^X}{d\theta} \quad \forall\theta \in \{\omega_{jt-1}, \eta_{jt}, \varepsilon_{jt}\} \tag{12}$$

Thus, the theoretical framework predicts that variations in historical productivity, ex-ante productivity shocks, and ex-post productivity shocks may influence (1) the firm's final revenue, (2) input allocations, and (3) the input's revenue elasticity. The combination of these effects yields the impact of changes in each productivity component on an input's MRP. Ultimately, combining the effects of each productivity component yields the total effect of a TFPR variation on an input's MRP.

The rationale is straightforward. Firms' past productivity levels influence the expected return on inputs, directly and through correlated distortions, and can affect price levels, which significantly impact input allocation and production decisions. While ex-post productivity shocks do not modify the firm's committed allocation of inputs and revenue elasticities[11], they do cause variations in final observed revenue. On the other hand, ex-ante productivity shocks can result in changes in the allocation of materials because firms incorporate new information about their productivity and adjust to fluctuations in the materials price level, thereby affecting observed revenue

[11]This is due to the additivity assumption in Equations (1) and (10).

and its elasticity to inputs.

The combined effect of these pathways determines the total impact of TFPR variation on the MRP of a given input for firm j at time t. Consequently, at the industry level, productivity dispersion—driven by period-to-period fluctuations in firm-level productivity and cross-firm differences in historical productivity levels—correlates with dispersion in the MRPs for any input. The next section focuses on quantifying this association after introducing the data used.

3. Data and Descriptive Statistics

I obtain annual firm-level harmonized balance sheet data for European manufacturing firms classified under NACE Rev. 2 code C from the Micro Data Infrastructure of the MICROPROD (MP) project[12]. Supported by the European Union, MICROPROD consolidates European microdata to provide insights for policymakers on growth and reform strategies and to evaluate economic efficiency. This effort relies on detailed data from Bureau van Dijk's ORBIS 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[13], conservative approximation for missing values, and identification of a *productivity sample* minimally subject to imputation enables desirable representativeness by closely replicating Eurostat's aggregate Struc-

[12] `https://cordis.europa.eu/project/id/822390`
[13] I.e., active or inactive.

tural Business Statistics[14]. 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 data directly (e.g. Asker, Collard-Wexler, and De Loecker (2014), Gopinath et al. (2017), Kalemli-Özcan et al. (2024)).

To approximate a firm's revenue (Y), I utilize the variable *Operating Revenue (Turnover)*, and for the workforce (L), I rely on the *Number of Employees*. Given that the MP dataset does not separately provide information on prices and quantities for intermediates and working capital, I deflate the *Cost of Materials* to approximate intermediates (M), and the *Total Fixed Assets* to approximate capital (K). The wage bill is derived from the variable *Cost of Employees*. Industry-level deflators (NACE Rev. 2, two-digit level) for intermediate inputs (to recover the quantity of materials) and gross output (to recover the capital stock) are sourced from the EU-KLEMS database.

Table 1 presents summary statistics for the main variables used in the analysis. The data reveals that the distributions of all variables are heavily right-skewed, as evidenced by the first three quartiles (Q1, Median, and Q3), indicating a large number of small firms and a few large firms. The minimum and maximum values confirm that the dataset includes both very small and very large firms. However, a comparison of medians and means across countries suggests that the samples of German and Polish firms still suffer from underrepresentation of smaller firms. This issue appears to be less pronounced for the other countries.

[14] 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	82,820	5,305	14,335	7,209	18,848	3,246
	SD	682,296	98,994	263,397	90,308	96,147	35,602
	Median	19,132	681	1,201	1,673	4,137	160
	Q1	5,390	261	399	679	1,523	49
	Q3	53,200	2,063	4,654	4,562	11,196	650
	Min	1	1	1	1	1	1
	Max	65,336,438	25,537,175	51,905,000	29,382,602	4,818,801	4,990,944
Cost of Materials, Th. Euros	Mean	51,540	3,459	7,336	3,945	12,132	1,936
	SD	1,201,597	85,857	181,084	68,914	72,588	27,217
	Median	7,946	305	331	644	2,051	62
	Q1	1,816	99	94	198	632	16
	Q3	25,716	1,073	1,704	2,077	6,406	281
	Min	1	1	1	1	1	1
	Max	298,700,068	23,475,881	36,833,000	24,205,783	4,239,812	4,192,198
Cost of Employees, Th. Euros	Mean	13,269	745	2,222	1,052	1,664	389
	SD	113,176	5,391	19,108	12,333	5,484	2,700
	Median	4,055	190	375	330	598	26
	Q1	1,287	80	142	133	223	8
	Q3	10,713	479	1,141	794	1,485	114
	Min	0	0	0	0	0	0
	Max	22,660,000	842,100	2,875,000	10,275,408	301,366	292,512
Fixed Assets, Th. Euros	Mean	23,210	1,980	3,644	2,284	7,112	1,516
	SD	177,734	29,474	98,443	36,201	42,499	13,156
	Median	2,589	180	167	314	1,034	41
	Q1	483	50	53	81	260	10
	Q3	9,852	644	589	1,164	3,403	195
	Min	1	1	1	1	1	1
	Max	20,739,803	5,867,352	17,469,000	12,144,733	2,420,068	956,784
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	38,383	17,284	49,425	33,636	14,600	18,456
Observations		76,403	1,000,134	606,514	1,261,767	55,581	168,393

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; *Cost of Employees*; *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.

4. Empirical Framework

4.1. Baseline - GNR

Building on the nonparametric approach of GNR, I adapt the model estimation to accommodate time-varying productivity dynamics. Additional details on this estimation procedure can be found in Supplemental Appendix A.1.

In stage one, I manipulate the first-order condition from the firm's problem in Equation (7) to derive an estimable nonlinear equation. Applying least squares yields two key outputs: materials revenue elasticities and firm-level ex-post productivity shocks. By integrating the estimated materials elasticity and subtracting it along with the estimated shocks from revenue, I uncover the sum of two unobserved components: the portion of revenue unrelated to materials and the persistent component of TFPR.

In stage two, I use polynomials to approximate the Markov process for the persistent component of TFPR and the remaining part of the revenue function. I estimate the polynomial parameters using the generalized method of moments (GMM), exploiting the orthogonality between past persistent productivity and the allocations of capital and labor inputs, and ex-ante shocks. The validity of the non-parametrically bootstrapped standard errors is discussed in Supplemental Appendix A.1.1.

Ultimately, the model's estimates allow the recovery of input elasticities, marginal revenue products, and productivity components at the firm-time level.

4.2. Factor Shares

Researchers widely use the FS method to determine MRPs and TFPR within the productivity and misallocation literature (see De Loecker and Syverson (2021) for a review). This technique generally assumes a production function characterized by constant returns to scale, where firms allocate labor and materials as flexible inputs after observing productivity. Under price-taking and cost minimization behaviors, the revenue elasticity for materials and labor equals

$$\text{elas}_{jt}^{X_{FS}} = \frac{P_{jt}^{X} X_{jt}}{Y_{jt}} \quad \forall X \in \{L, M\}, \tag{13}$$

for labor and materials, and

$$\text{elas}_{jt}^{K_{FS}} = 1 - \text{elas}_{jt}^{M_{FS}} - \text{elas}_{jt}^{L_{FS}}, \tag{14}$$

for capital[15], where P_{jt}^{X} and X_{jt} denote the price and quantity of input X for firm j in period t, and Y_{jt} signifies revenue.

Then, using a first-order Taylor Series expansion of the log revenue function, one can estimate TFPR as:

$$\nu_{jt}^{FS} = y_{jt} - \text{elas}_{jt}^{K_{FS}} k_{jt} - \text{elas}_{jt}^{L_{FS}} l_{jt} - \text{elas}_{jt}^{M_{FS}} m_{jt}, \tag{15}$$

[15]Certain studies, such as Asker, Collard-Wexler, and De Loecker (2014), contemplate firms possessing market power, facing a demand schedule with constant elasticity ζ. In this context, assuming a Cobb-Douglas production specification and profit maximization, the revenue elasticity of capital is expressed as:

$$\text{elas}_{jt}^{K_{FS}} = \frac{\zeta - 1}{\zeta} - \text{elas}_{jt}^{M_{FS}} - \text{elas}_{jt}^{L_{FS}}.$$

Nevertheless, this scenario is excluded from the current analysis as it does not influence elasticities dispersion.

where ν_{jt}^{FS} represents the factor shares-based TFPR.

Finally, one can decompose TFPR into two additive components:

$$\nu_{jt}^{FS} = \nu_{jt-1}^{FS} + \left(\nu_{jt}^{FS} - \nu_{jt-1}^{FS}\right). \tag{16}$$

Similar to the baseline-GNR approach, one can assume that ν_{jt-1}^{FS} is known to firm j when allocating any time t inputs. On the other hand, the component $\left(\nu_{jt}^{FS} - \nu_{jt-1}^{FS}\right)$ may remain unobserved during capital allocation (see, for example, Asker, Collard-Wexler, and De Loecker (2014)). I refer to this as the *shock* component.

The GNR framework and the FS approach share several key assumptions, with the former nearly nesting the latter. Both methodologies posit *a* production function with log-additive productivity components and assume price-taking behavior by firms. Neither specifies the capital allocation problem faced by firms. However, the FS approach imposes additional restrictions on the GNR framework. The FS approach assumes the absence of ex-post productivity shocks, imposes constant returns to scale (which GNR leaves unrestricted), and treats labor, like materials, as a flexible input allocated under perfect information on period's productivity. Conversely, the GNR framework enriches the productivity process by imposing a Markov structure, whereas the FS approach leaves this unrestricted.

5. Results and Discussion

5.1. Production Function Estimates: A Comparison

In the baseline-GNR framework, I allow the productivity Markov process $m_t(.)$ to vary across five historical periods: *Beginning 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 data availability constraints, productivity parameters for the 2001–2003 period are only estimated for Spain, France, and Italy. I estimate the production function separately for each country-industry pair[16]. To compute standard errors, I employ a non-parametric clustered bootstrap procedure. This involves drawing with replacement from the pool of firm identifiers 100 times.

The estimation results of the baseline-GNR model are presented in Supplemental Appendix B.1, which also includes a comprehensive discussion. The remainder of this subsection focuses on comparing the baseline-GNR and FS approaches, particularly in terms of the distribution and patterns of the estimates for the inputs' revenue elasticities, MRPs, and TFPR.

In Table 2, I compare the moments from the pooled empirical distributions of revenue elasticities and returns to scale estimated using the baseline-GNR approach and the FS method[17]. The FS approach tends to overestimate both the dispersion and the average revenue elasticity of capital and materials while underestimating both the average and the dispersion of the revenue elasticity of labor. Subsection C.1 of the Supplemental Appendix further corroborates these patterns, where I compare the country-specific empirical distributions of revenue elasticities obtained using the baseline-

[16]The industries, with their corresponding Nace Rev2 codes, are: Food, beverages and tobacco (10, 11, 12); Textiles, apparel and leather (13, 14, 15); Wood, paper, and printing (16, 17, 18); Coke, chemicals, and pharmaceuticals (19, 20, 21); Rubber, plastics, metallic and non-metallic mineral products, fabricated metal products (22, 23, 24, 25); Electronic, optical products and electrical equipment (26, 27); Machinery, motor vehicles and other transport equipment (28, 29, 30); Furniture and other manufacturing (31, 32, 33).

[17]The difference in sample size between the two approaches stems from missing data and negative estimated elasticities. To compute the revenue elasticity for labor using the FS approach, I use the variable *Cost of Employees* from MP. However, 22,119 firms do not report wages. Additionally, using FS, I estimate negative capital elasticities for 115,447 firms, which are excluded from the analysis.

GNR approach with those derived from the FS method.

TABLE 2. GNR vs Factor Shares: Elasticity Distributions Statistics

	$elas^K$		$elas^L$		$elas^M$		*Returns to Scale*	
Statistic	GNR	Factor Shares	GNR	Factor Shares	GNR	Factor Shares	GNR	Factor Shares
Mean	0.18	0.32	0.45	0.26	0.31	0.42	0.95	1.00
Median	0.16	0.30	0.47	0.23	0.30	0.42	0.97	1.00
SD	0.12	0.16	0.21	0.15	0.17	0.20	0.17	0.00
Skewness	0.98	0.74	-0.38	0.82	0.62	0.07	-0.30	
Kurtosis	3.07	0.69	2.22	0.62	1.56	-0.56	10.20	
N	3,168,792	3,031,226	3,168,792	3,031,226	3,168,792	3,031,226	3,168,792	3,168,792

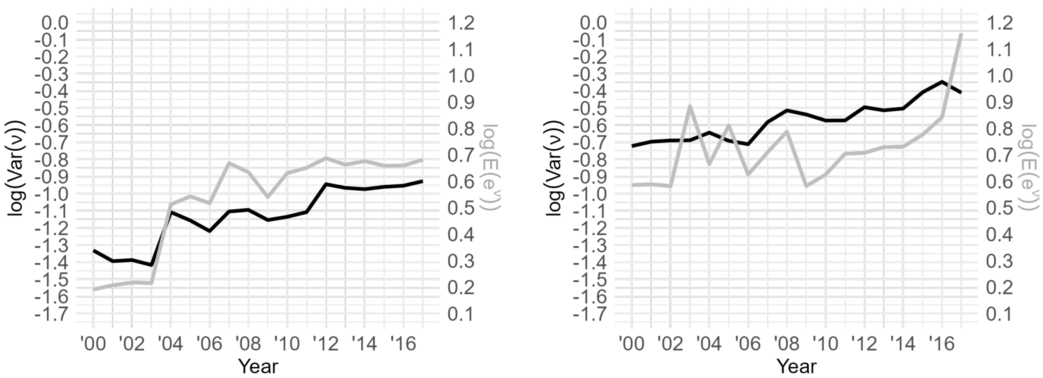
This table presents summary statistics for the pooled empirical distributions of the revenue elasticity of capital ($elas^K$), labor ($elas^L$), materials ($elas^M$), and returns to scale, estimated using the baseline approach (*GNR*) or using factor shares. The table displays the mean, the median, the standard deviation (SD), skewness, and kurtosis. The final row presents the sample size.

To calculate aggregate TFPR and (log) MRP dispersion statistics, I compute a weighted average of the country-industry-year-specific variances for these variables. The weights correspond to each industry's annual share of the country's manufacturing revenue, renormalized to sum to unity by year. Figure 1 illustrates the temporal evolution of aggregate TFPR dispersion along with the weighted average TFPR level, estimated using both the baseline-GNR and FS approaches. Additionally, Figure 2 depicts the evolution of aggregate dispersion for capital, labor, and materials MRP over time, comparing results from both methodologies.

Figure 1 reveals that both approaches demonstrate increasing trends in the aggregate mean and dispersion of TFPR. However, the FS approach exhibits a more erratic time pattern for the aggregate mean compared to the baseline-GNR. Moreover, the FS method consistently overestimates both the aggregate mean and variance of TFPR throughout the observed period.

Finally, regarding Figure 2, it appears that the FS approach yields patterns and levels of aggregate capital MRP dispersion that are strikingly similar to those of the baseline-GNR approach across years. In contrast, for mate-

FIGURE 1. TFPR Dispersion and Mean Evolution

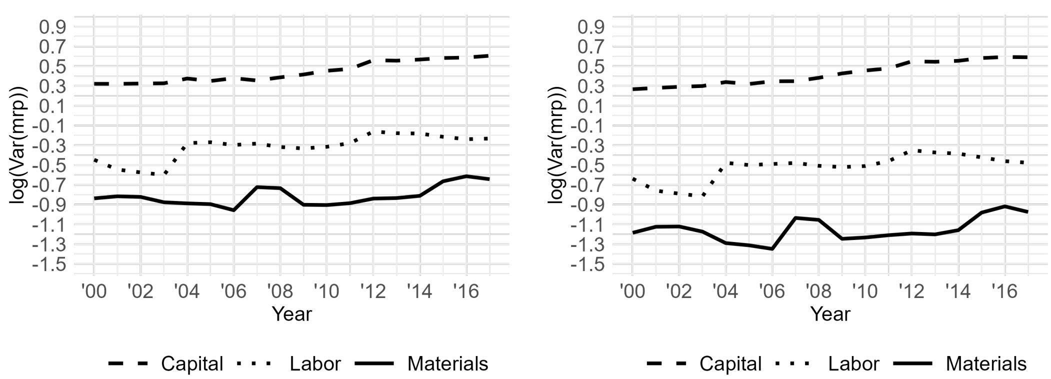


A. Baseline - GNR

B. Factor Shares

The solid black line in Figure 1 displays the evolution of the (log) aggregate variance for TFPR, ν. The solid gray line shows the (log) average value of TFPR *in levels*, reported on the secondary y-axis. I pool variances and means by taking a weighted average of the country-industry-year-specific variances and means, using the industry's annual share of the country's manufacturing revenue, renormalized to sum to unity by year, as weights.

FIGURE 2. Inputs MRP Dispersion Evolution



A. Baseline - GNR

B. Factor Shares

Figure 2 displays the evolution of the pooled (log) aggregate variance for the inputs' log marginal revenue products. The inputs shown are materials (solid black line), capital (dashed black line), and labor (dotted black line). I pool the log variances by taking a weighted average of the country-industry-year-specific variances, using the industry's annual share of the country's manufacturing revenue, renormalized to sum to unity by year, as weights.

rials and labor, while the temporal dynamics are comparable between the two approaches, the FS method systematically underestimates the level of aggregate MRP dispersion by 20% for labor and 30% for materials.

Intuitively, these results suggest that the FS approach attributes a portion of the MRP variance for materials and labor to the variance of TFPR, in contrast to the baseline-GNR. These patterns are further corroborated in Supplemental Appendix C.2, where I present the aforementioned trends at the country-year level for both the baseline-GNR and the FS approach, accompanied by a detailed description.

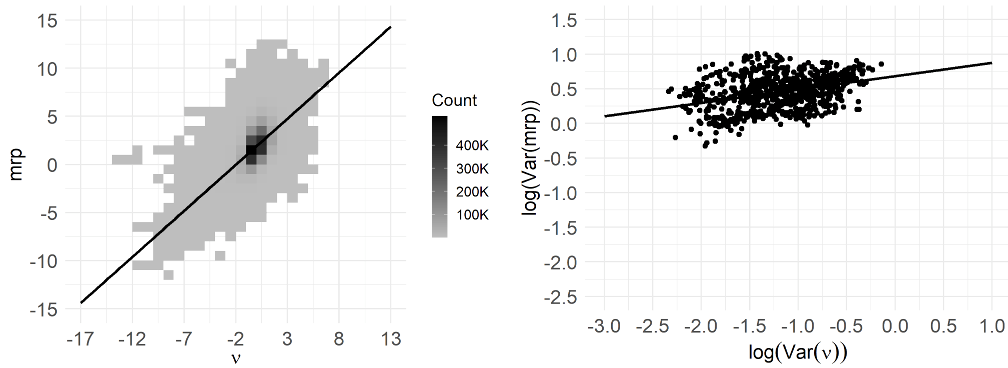
In the next section, I empirically assess the association between MRP dispersion and TFPR variability.

5.2. Evaluating the Association of Inputs MRP Dispersion to TFPR Variability

Figures 3, 4, and 5 provide initial visual evidence on the relationship between MRP and TFPR, estimated using the baseline-GNR approach, for each input using the full pooled dataset. Panel A in each figure presents a binscatter plot of the log MRP for each input (y-axis) against TFPR (x-axis), with the fitted linear regression line displayed as a solid black line. For capital and labor, an increasing relationship is evident, with estimated slope coefficients of 0.96 and 0.79, respectively. The relationship appears weaker for materials, with a coefficient of 0.10.

Panel B in each figure displays scatter plots of the log variance of log MRP for each input (y-axis) against the log variance of TFPR (x-axis) at the country-industry-time level, again with the fitted linear regression line shown. A 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 compared to capital, with slope coefficients of 0.56 and 0.19, respectively.

FIGURE 3. TFPR - MRP Correlation: Capital



A B

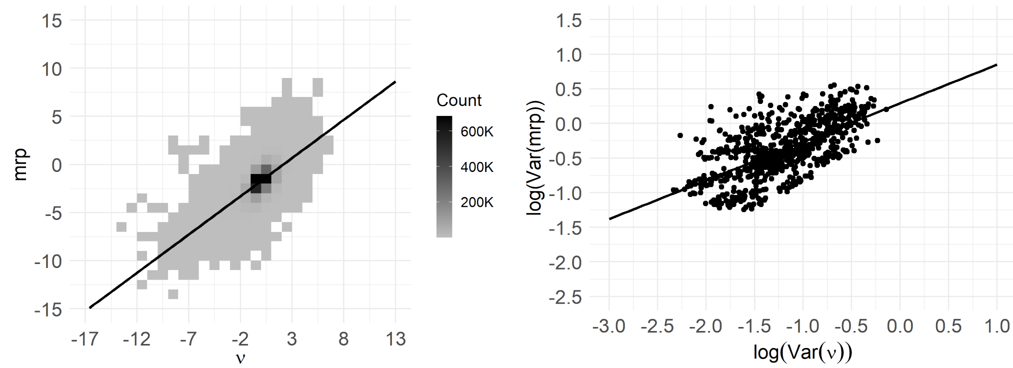
Panel A displays a binscatterplot of the log marginal revenue product (MRP) for capital (y-axis) against TFPR (x-axis) for 3,168,792 firm-time observations. The color intensity indicates the number of observations per bin, with thousands indicated by "K" (see legend). The solid line is a fitted regression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

While these visualizations provide evidence of correlation in terms of levels and dispersions, a simple pooled linear regression has two key limitations. First, it fails to capture the potentially heterogeneous sensitivity across countries, time periods, and industries, and to control for unobservable country-, time-, and industry-specific characteristics. Second, it does not account for the specific impacts of TFPR shocks or past productivity heterogeneity on MRP variance.

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

$$\log(Var_{st}(mrp^{X}_{jt})) = c + \beta \log(Var_{st}(\nu_{jt})) + e_{jt} \tag{17}$$

FIGURE 4. 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.

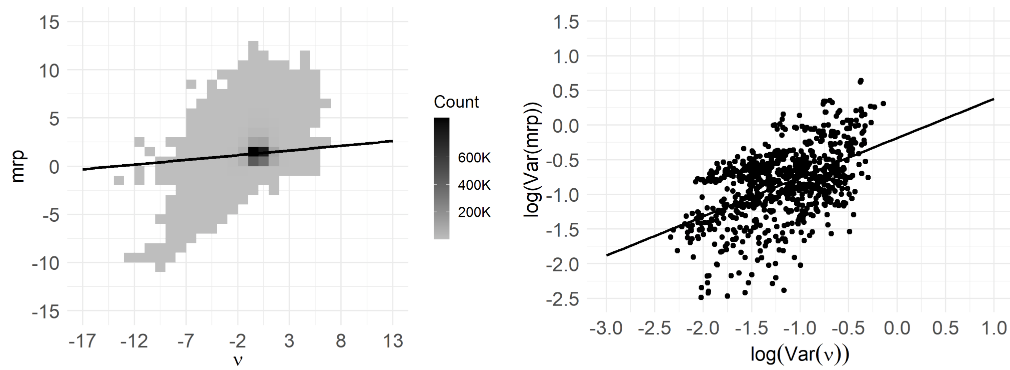
$$\log(Var_{st}(mrp^X_{jt})) = \iota_s + \iota_t + \beta \log(Var_{st}(\nu_{jt})) + e_{jt} \tag{18}$$

where $Var_{st}(mrp^X_{jt})$ is the variance at the sector-time level of the (log) MRP for input X and $Var_{st}(\nu_{jt})$ is the dispersion of TFPR at the same level of aggregation[18], while e_{jt} is the residual of the linear regression model.

The model in Equation (17) is a simple linear regression, whereas the model in Equation (18) includes industry and time fixed effects, ι_s and ι_t, respectively. For each model, the observations are weighted by the average industry revenue share of the country's total manufacturing revenue. Given that the variables are generated in a previous step, I compute standard errors using non-parametric clustered bootstrap, resampling the firms' identifiers. The regression results by country are reported in Table 3.

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

FIGURE 5. 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.

The coefficient β in both models estimates the average elasticity of MRP dispersion with respect to TFPR variance. The parameter estimates for the simple model in Equation (17) (reported in Specification 1) are generally positive and highly statistically significant. However, the estimated β increases on average in the augmented model in Equation (18) for capital and materials, and decreases for labor (reported in Specification 2), indicating bias in the simpler model due to unobserved sector and time-specific effects. This is expected since production technologies and shocks differ across sectors and years, creating omitted variable bias. With industry and year fixed effects accounting for these differences, Specification 2 is preferred.

Using the baseline-GNR approach, I estimate a statistically significant average elasticity of MRP dispersion with respect to TFPR variance of 0.30 for capital, 0.41 for labor, and 0.55 for materials. The results exhibit substantial heterogeneity across countries. Repeating the analysis using estimates for

TABLE 3. TFPR Regression Results

	Capital				Labor				Materials			
	Baseline - GNR		Factor Shares		Baseline - GNR		Factor Shares		Baseline - GNR		Factor Shares	
Specification	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Germany												
β	0.185	0.145	0.119	0.133	0.675	0.497	-0.636	0.355	0.722	0.630	-0.082	0.958
	(0.072)	(0.049)	(0.096)	(0.066)	(0.343)	(0.034)	(0.427)	(0.204)	(0.109)	(0.165)	(0.503)	(0.185)
N	112	112	112	112	112	112	112	112	112	112	112	112
R^2	0.279	0.768	0.062	0.658	0.336	0.965	0.103	0.950	0.510	0.705	0.002	0.728
RMSE	0.155	0.071	0.118	0.066	0.378	0.096	0.394	0.108	0.428	0.272	0.694	0.321
Spain												
β	0.349	0.252	0.580	0.255	0.663	0.357	-0.509	0.150	0.373	0.448	1.132	1.459
	(0.088)	(0.055)	(0.077)	(0.096)	(0.134)	(0.053)	(0.368)	(0.110)	(0.167)	(0.181)	(0.316)	(0.413)
N	144	144	144	144	144	144	144	144	144	144	144	144
R^2	0.315	0.973	0.555	0.953	0.494	0.989	0.162	0.981	0.181	0.917	0.532	0.914
RMSE	0.176	0.038	0.123	0.041	0.215	0.039	0.248	0.041	0.298	0.100	0.258	0.123
France												
β	0.210	0.453	0.235	0.535	0.754	0.659	0.082	0.516	-0.218	0.085	1.405	0.250
	(0.155)	(0.091)	(0.118)	(0.126)	(0.194)	(0.089)	(0.595)	(0.113)	(0.399)	(0.277)	(0.537)	(0.415)
N	144	144	144	144	144	144	144	144	144	144	144	144
R^2	0.231	0.921	0.124	0.847	0.601	0.983	0.002	0.962	0.058	0.909	0.424	0.919
RMSE	0.132	0.044	0.112	0.052	0.217	0.046	0.325	0.067	0.394	0.088	0.264	0.103
Italy												
β	0.208	-0.017	0.300	0.322	0.635	0.173	-0.080	0.792	0.162	0.438	1.014	0.723
	(0.100)	(0.128)	(0.179)	(0.231)	(0.206)	(0.452)	(0.389)	(0.528)	(0.323)	(0.165)	(0.084)	(0.431)
N	144	144	144	144	144	144	144	144	144	144	144	144
R^2	0.167	0.952	0.320	0.962	0.499	0.859	0.009	0.944	0.034	0.953	0.862	0.964
RMSE	0.173	0.037	0.131	0.034	0.199	0.106	0.271	0.067	0.317	0.080	0.148	0.076
Poland												
β	0.456	0.370	0.563	0.420	0.294	0.419	0.035	0.319	0.615	0.471	1.197	1.124
	(0.052)	(0.029)	(0.092)	(0.066)	(0.077)	(0.038)	(0.061)	(0.144)	(0.089)	(0.137)	(0.125)	(0.315)
N	112	112	112	112	112	112	112	112	112	112	112	112
R^2	0.636	0.930	0.674	0.943	0.328	0.901	0.005	0.777	0.426	0.723	0.716	0.812
RMSE	0.160	0.088	0.239	0.087	0.199	0.088	0.227	0.113	0.421	0.284	0.365	0.297
Romania												
β	0.264	0.381	0.265	0.120	0.083	0.266	-0.045	-0.021	1.626	1.105	1.606	1.348
	(0.152)	(0.057)	(0.090)	(0.093)	(0.216)	(0.058)	(0.064)	(0.084)	(0.257)	(0.185)	(0.202)	(0.252)
N	112	112	112	112	112	112	112	112	112	112	112	112
R^2	0.168	0.912	0.290	0.898	0.029	0.864	0.018	0.783	0.638	0.970	0.817	0.966
RMSE	0.210	0.068	0.204	0.072	0.188	0.058	0.183	0.073	0.409	0.128	0.363	0.166
Pooled												
β	0.224	0.298	0.282	0.283	0.567	0.409	0.133	0.286	0.497	0.550	0.916	1.083
	(0.065)	(0.038)	(0.065)	(0.054)	(0.081)	(0.033)	(0.132)	(0.097)	(0.095)	(0.078)	(0.131)	(0.143)
N	768	768	768	768	768	768	768	768	768	768	768	768
R^2	0.201	0.950	0.242	0.943	0.434	0.967	0.017	0.965	0.263	0.908	0.422	0.922
RMSE	0.234	0.061	0.210	0.061	0.305	0.078	0.384	0.082	0.441	0.175	0.493	0.197
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 variance of (log) MRP for each input on TFPR dispersion by country. *Baseline - GNR* and *Factor Shares* refer to the methodologies used to estimate TFPR and MRPs. Specification 1 refers to the simple linear model in Equation (17) and Specification 2 refers to the model with industry and year fixed effects in Equation (18). In both models, the observations are weighted by the industry's average revenue share of total manufacturing revenue. Reported are the estimates for the slope coefficient (β), the number of industry-year observations (N), unadjusted R^2, and root mean squared error (RMSE). Standard errors, computed using clustered non-parametric bootstrap over 500 repetitions, are in parentheses. For the pooled regression, I use country-sector and country-year fixed effects, and the weights are normalized to sum to unity by year.

TFPR and MRP recovered via the FS approach, I find that this method underestimates the elasticity for capital (0.28) and labor (0.29) while overestimating it for materials (1.08). The bias is more pronounced for materials and labor, while it is minor for capital.

The interpretation of the FS approach estimates for materials and labor warrants caution. Unlike the baseline methodology, the FS approach assumes that firms allocate materials and labor with perfect information about productivity shocks. Consequently, for these inputs, this approach excludes unexpected ex post shocks to contemporaneous productivity that could lead to misallocation. Therefore, the strong positive correlation observed is attributed entirely to known productivity heterogeneity. Nonetheless, reporting these estimates is instructive for highlighting the limitations researchers encounter when studying the link between productivity dispersion and misallocation using the FS approach.

My findings in this section confirm and extend the results from Asker, Collard-Wexler, and De Loecker (2014), who demonstrated that industries with greater time-series volatility of productivity exhibit greater cross-sectional dispersion of the marginal revenue product of capital[19]. They were the first to identify productivity volatility as a key driver of capital MRP dispersion. This paper builds on their work by expanding the investigation to encompass all production inputs, including materials, and demonstrates that productivity dispersion accounts for MRP dispersion across all inputs.

The theoretical framework in Section 2.1 enables an additional contribution: decomposing estimated TFPR into its observed and shock components.

[19] My estimated slope coefficients using FS are lower than those reported by Asker, Collard-Wexler, and De Loecker (2014) in their Table 3. This divergence stems from several methodological factors: 1) industry definitions vary, and 2) the authors regress MRP dispersion on TFPR *volatility*, whereas I focus on TFPR *variance*.

Given the timing assumptions on input allocation, each input's MRP dispersion may exhibit heterogeneous sensitivity to the variability of these different components. Investigating this heterogeneous relationship is the focus of the final results section.

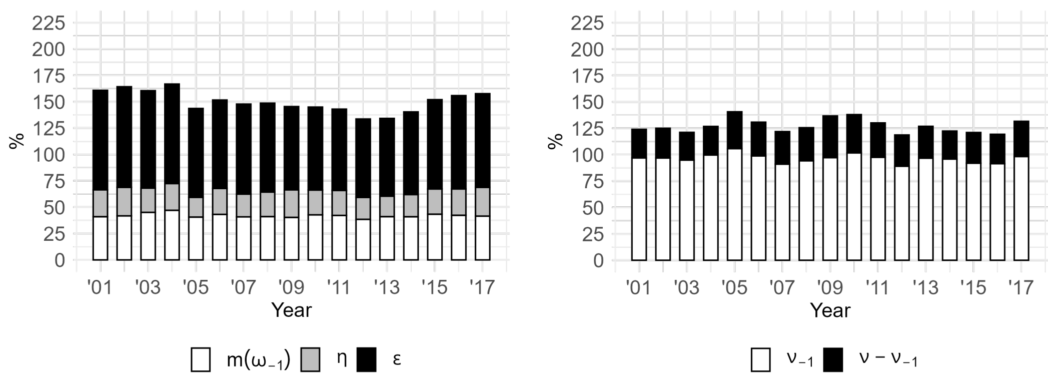
5.3. Evaluating the Association of Input MRP Dispersion to TFPR Components Variability

In the baseline-GNR model, the three TFPR components—past productivity, ex ante shocks, and ex post shocks—are theoretically assumed to be orthogonal. However, Figure 6A reveals that the observed sums of total TFPR variance shares deviate from one, indicating non-zero covariances between the TFPR components at the industry level. This implies that these components are correlated in the data, contrary to the theoretical assumption. Similarly, Figure 6B shows traces of correlation between observed and shock TFPR components for the factor share approach. Supplemental Appendix D, Figures A7 and A8 present the corresponding plots for each country.

Notably, in the baseline-GNR approach, the majority of industry TFPR variation is driven by ex post productivity shocks (ε), while ex ante shocks (η) contribute the least. Past persistent productivity (ω_{-1}) falls in between, accounting for a moderate share on average. Overall, for the baseline-GNR approach, shocks dispersion dominates productivity heterogeneity. This pattern is reversed in the FS approach: Figure 6B demonstrates that heterogeneity in past productivity is much larger than the variability in the shock component by a factor of four.

The FS approach appears to overestimate the weight of past productivity and underestimate the weight of productivity shock dispersion in total

FIGURE 6. Component Shares of TFPR Variance



A. Baseline - GNR

B. Factor Shares

This figure illustrates the annual weighted average share of country-industry-year TFPR variance attributable to each TFPR component. The decompositions are derived from equation (10) for Figure 6 and from equation (16) for Figure 6B. The weights are based on each industry's share of total annual manufacturing revenue in its respective country, normalized to sum to one each year.

productivity heterogeneity. This discrepancy is further corroborated in Supplemental Appendix D, where Tables A9 and A10 present the weighted average share of country-industry-year inputs' MRP dispersion for each TFPR component variance, for the baseline-GNR and FS approaches, respectively.

To examine the heterogeneous sensitivity of input MRPs dispersion to TFPR components variances across countries, I estimate the following linear models separately for each country:

(19)

$$\begin{aligned}\log(Var_{st}(mrp^X_{jt})) =& c + \beta_{\omega_{-1}} \log(Var_{st}(\omega_{jt-1})) + \beta_\eta \log(Var_{st}(\eta_{jt})) \\ &+ \beta_\varepsilon \log(Var_{st}(\varepsilon_{jt})) + \sum_{z\in\{(\omega_{-1},\eta),(\omega_{-1},\varepsilon),(\eta,\varepsilon)\}} \beta_z \log(1+\rho_{z,st}) + e_{jt}\end{aligned}$$

(20)

$$\begin{aligned}\log(Var_{st}(mrp^X_{jt})) =& \iota_s + \iota_t + \beta_{\omega_{-1}} \log(Var_{st}(\omega_{jt-1})) + \beta_\eta \log(Var_{st}(\eta_{jt})) \\ &+ \beta_\varepsilon \log(Var_{st}(\varepsilon_{jt})) + \sum_{z\in\{(\omega_{-1},\eta),(\omega_{-1},\varepsilon),(\eta,\varepsilon)\}} \beta_z \log(1+\rho_{z,st}) + e_{jt}\end{aligned}$$

Again, here ω_{jt-1} denotes the past persistent productivity component,

η_{jt} represents the ex-ante shock, and ε_{jt} represents the ex-post shock. To avoid omitted variable biases arising from functional dependence between variables, I include as regressors the log transformations of the Pearson correlation coefficients at the industry-time level: $\rho_{(\omega_{-1},\eta),st}$, $\rho_{(\omega_{-1},\varepsilon),st}$, and $\rho_{(\eta,\varepsilon),st}$. The residual of the model is denoted by e_{jt}.

The model in Equation (20) further incorporates industry and year fixed effects, ι_s and ι_t, respectively. Observations are weighted by average annual industry revenue shares. Given the first-stage generated variables, I compute standard errors using individual-level clustered bootstrap. The country-specific results are presented in Table 4.

The coefficients $\beta_{\omega_{-1}}$, β_{η}, and β_{ε} estimate the average elasticities of an input MRP dispersion to the variances of pre-existing productivity heterogeneity, ex-ante productivity shocks, and ex-post productivity shocks, respectively. For all inputs, these coefficients change after controlling for industry-year fixed effects, suggesting that Specification 1 suffers from bias due to unobserved sector- and year-specific effects. Therefore, I take Specification 2, which includes industry and year fixed effects, as the baseline.

For all inputs' MRP dispersions, the ex-post shock (ε) demonstrates the highest sensitivity, with overall elasticities of 0.14 for capital, 0.21 for labor, and 0.69 for materials. In contrast, pre-existing productivity (ω_{-1}) and ex-ante shock (η) dispersions exhibit milder effects. The overall elasticity to pre-existing productivity dispersion is estimated at 0.05 for capital, 0.06 for labor, and 0.02 for materials. Similarly, the overall elasticity to ex-ante shock dispersion is estimated at 0.06 for capital, and 0.03 for both labor and materials. There is significant cross-country heterogeneity in the estimates, ranging from negative or small, insignificant effects to large and highly significant effects.

TABLE 4. TFPR Components Regression Results - Baseline-GNR

	Germany		Spain		France		Italy		Poland		Romania		Pooled	
Spec.	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(1)	(1)	(2)
Capital														
$\beta_{\omega_{-1}}$	-0.023	-0.073	-0.186	0.007	0.029	-0.071	0.087	-0.133	0.014	0.116	0.104	0.080	0.030	0.051
	(0.080)	(0.032)	(0.143)	(0.055)	(0.110)	(0.066)	(0.183)	(0.050)	(0.077)	(0.046)	(0.093)	(0.046)	(0.075)	(0.033)
β_{η}	0.067	0.047	0.036	-0.007	0.048	0.120	0.128	0.099	0.085	0.046	-0.077	0.029	0.002	0.058
	(0.044)	(0.032)	(0.139)	(0.023)	(0.120)	(0.067)	(0.140)	(0.032)	(0.040)	(0.037)	(0.079)	(0.069)	(0.047)	(0.019)
β_{ε}	0.122	0.064	0.489	0.231	0.324	0.158	0.019	0.155	0.423	0.207	0.335	0.234	0.202	0.143
	(0.061)	(0.042)	(0.137)	(0.051)	(0.102)	(0.078)	(0.260)	(0.066)	(0.062)	(0.055)	(0.080)	(0.072)	(0.060)	(0.032)
N	104	104	136	136	136	136	136	136	104	104	104	104	720	720
R^2	0.326	0.773	0.550	0.982	0.450	0.917	0.196	0.969	0.661	0.908	0.226	0.915	0.195	0.945
RMSE	0.163	0.070	0.157	0.035	0.114	0.048	0.171	0.030	0.171	0.098	0.191	0.062	0.233	0.063
Labor														
$\beta_{\omega_{-1}}$	0.005	0.058	0.496	0.084	0.503	0.005	0.754	0.087	0.068	0.071	0.045	0.040	0.191	0.061
	(0.412)	(0.096)	(0.190)	(0.045)	(0.201)	(0.093)	(0.187)	(0.189)	(0.077)	(0.046)	(0.122)	(0.057)	(0.103)	(0.031)
β_{η}	0.054	0.042	-0.145	0.078	-0.249	0.040	-0.497	-0.128	0.083	0.038	0.021	0.051	0.048	0.027
	(0.108)	(0.025)	(0.236)	(0.044)	(0.167)	(0.047)	(0.170)	(0.074)	(0.054)	(0.032)	(0.050)	(0.031)	(0.070)	(0.021)
β_{ε}	0.443	0.224	0.374	0.188	0.367	0.193	0.205	-0.355	0.219	0.255	0.019	0.168	0.292	0.214
	(0.188)	(0.050)	(0.189)	(0.063)	(0.220)	(0.081)	(0.288)	(0.381)	(0.089)	(0.073)	(0.106)	(0.049)	(0.079)	(0.038)
N	104	104	136	136	136	136	136	136	104	104	104	104	720	720
R^2	0.281	0.960	0.644	0.989	0.629	0.981	0.658	0.902	0.337	0.888	0.131	0.860	0.410	0.965
RMSE	0.381	0.100	0.198	0.036	0.218	0.052	0.174	0.090	0.216	0.098	0.180	0.058	0.309	0.080
Materials														
$\beta_{\omega_{-1}}$	-0.017	-0.123	-0.063	0.313	-0.221	0.066	-0.420	0.114	0.077	0.043	0.131	0.018	0.022	0.022
	(0.147)	(0.135)	(0.261)	(0.206)	(0.313)	(0.072)	(0.278)	(0.069)	(0.107)	(0.074)	(0.076)	(0.072)	(0.078)	(0.049)
β_{η}	0.001	0.061	-0.112	-0.085	-0.080	0.074	-0.401	-0.066	-0.007	0.011	-0.082	0.062	-0.128	0.025
	(0.097)	(0.046)	(0.221)	(0.083)	(0.303)	(0.037)	(0.276)	(0.052)	(0.083)	(0.060)	(0.095)	(0.059)	(0.060)	(0.028)
β_{ε}	0.621	0.637	0.730	0.495	0.673	0.493	1.142	0.567	0.866	0.879	1.136	0.889	0.756	0.689
	(0.090)	(0.079)	(0.230)	(0.133)	(0.219)	(0.132)	(0.500)	(0.084)	(0.096)	(0.108)	(0.127)	(0.179)	(0.077)	(0.059)
N	104	104	136	136	136	136	136	136	104	104	104	104	720	720
R^2	0.720	0.905	0.367	0.947	0.424	0.968	0.492	0.978	0.703	0.889	0.916	0.977	0.585	0.955
RMSE	0.332	0.169	0.271	0.076	0.279	0.056	0.240	0.058	0.296	0.186	0.182	0.099	0.327	0.122
Constant	YES	NO	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	NO	YES

The table presents regression results of the dispersion of (log) MRP for each input on TFPR components variation by country. Variables are recovered using the baseline-GNR approach. Specification 1 refers to the simple linear model (19) and Specification 2 refers to the model with industry and year fixed effects (20). In both models, the observations are weighted by the industry average revenue share of total annual manufacturing revenue. Reported are the 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 pooled regression, I use country-sector and country-year fixed effects, and the weights are normalized to sum to unity by year.

The FS approach enables a similar decomposition of TFPR into observed and shock components. I estimate the following linear models separately for each country:

$$\log(Var_{st}(mrp^X_{jt})) = c + \beta_{\nu_{-1}} \log(Var_{st}(\nu^{FS}_{jt-1})) + \beta_{\nu-\nu_{-1}} \log(Var_{st}(\nu^{FS}_{jt} - \nu^{FS}_{jt-1})) + \beta_{(\nu_{-1},\nu-\nu_{-1})} \log(1 + \rho_{(\nu_{-1},\nu-\nu_{-1}),st}) + e_{jt} \tag{21}$$

$$\log(Var_{st}(mrp^X_{jt})) = \iota_s + \iota_t + \beta_{\nu_{-1}} \log(Var_{st}(\nu^{FS}_{jt-1})) + \beta_{\nu-\nu_{-1}} \log(Var_{st}(\nu^{FS}_{jt} - \nu^{FS}_{jt-1})) + \beta_{(\nu_{-1},\nu-\nu_{-1})} \log(1 + \rho_{(\nu_{-1},\nu-\nu_{-1}),st}) + e_{jt} \tag{22}$$

Here, ν^{FS}_{jt-1} represents the past productivity component of TFPR, and $(\nu^{FS}_{jt} - \nu^{FS}_{jt-1})$ represents the shock component. To avoid omitted variable biases, I control for covariances between variables by including as regressors the log transformations of the Pearson correlation coefficients at the industry-time level: $\rho_{(\nu_{-1},\nu-\nu_{-1}),st}$. The residual of the model is denoted by e_{jt}.

The model in Equation (22) incorporates industry and year fixed effects, ι_s and ι_t. Observations are weighted by average annual industry revenue shares. I compute standard errors using individual-level clustered bootstrap, given the first-stage generated variables. The country-specific results are presented in Table 5.

The results for capital suggest that a regression using FS estimates overestimates the elasticity of the input's MRP dispersion to pre-existing productivity heterogeneity (ν_{-1}), with an overall sensitivity of 0.15, compared to the baseline-GNR estimates. Conversely, it underestimates the sensitivity to the shock dispersion ($\nu - \nu_{-1}$), with an overall sensitivity of 0.08. There is also significant cross-country heterogeneity[20].

[20] My estimates of $\beta_{\nu-\nu_{-1}}$ for capital for France, Spain, and Romania, though positive, are much smaller than those reported in Table 3 of Asker, Collard-Wexler, and De Loecker (2014).

TABLE 5. TFPR Components Regression Results - Factor Shares

	Germany		Spain		France		Italy		Poland		Romania		Pooled	
Spec.	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(1)	(1)	(2)
Capital														
$\beta_{\gamma_{-1}}$	0.036	0.007	0.513	-0.008	0.262	0.532	0.205	0.283	0.393	0.299	0.241	-0.074	0.300	0.148
	(0.167)	(0.105)	(0.158)	(0.151)	(0.131)	(0.174)	(0.236)	(0.254)	(0.211)	(0.115)	(0.120)	(0.133)	(0.088)	(0.072)
$\beta_{\gamma-\gamma_{-1}}$	0.034	0.020	0.077	0.257	-0.040	0.046	0.030	0.100	0.126	0.050	-0.013	0.228	-0.016	0.084
	(0.050)	(0.027)	(0.126)	(0.117)	(0.126)	(0.060)	(0.180)	(0.041)	(0.120)	(0.060)	(0.098)	(0.105)	(0.046)	(0.035)
N	104	104	136	136	136	136	136	136	104	104	104	104	720	720
R^2	0.089	0.702	0.626	0.962	0.149	0.834	0.381	0.966	0.546	0.929	0.305	0.917	0.229	0.941
RMSE	0.125	0.066	0.113	0.038	0.109	0.053	0.125	0.032	0.246	0.087	0.191	0.067	0.209	0.060
Labor														
$\beta_{\gamma_{-1}}$	-0.762	0.334	0.631	0.110	0.709	0.567	0.417	0.444	0.169	0.188	-0.005	-0.300	0.117	0.145
	(0.600)	(0.191)	(0.116)	(0.148)	(0.320)	(0.162)	(0.463)	(0.595)	(0.147)	(0.191)	(0.081)	(0.103)	(0.190)	(0.115)
$\beta_{\gamma-\gamma_{-1}}$	-0.237	-0.003	-0.870	0.010	-0.797	-0.065	-0.656	0.120	-0.196	0.021	-0.087	0.152	-0.029	0.038
	(0.182)	(0.050)	(0.187)	(0.083)	(0.230)	(0.039)	(0.298)	(0.068)	(0.154)	(0.096)	(0.039)	(0.081)	(0.146)	(0.034)
N	104	104	136	136	136	136	136	136	104	104	104	104	720	720
R^2	0.229	0.950	0.814	0.982	0.612	0.964	0.287	0.949	0.074	0.819	0.071	0.851	0.024	0.968
RMSE	0.397	0.110	0.131	0.040	0.218	0.063	0.245	0.064	0.237	0.101	0.183	0.066	0.388	0.080
Materials														
$\beta_{\gamma_{-1}}$	-0.246	0.780	0.841	1.511	0.781	-0.013	1.045	0.776	1.021	0.903	0.573	0.196	0.905	0.648
	(0.647)	(0.284)	(0.473)	(0.566)	(0.229)	(0.527)	(0.178)	(0.456)	(0.223)	(0.469)	(0.167)	(0.178)	(0.149)	(0.197)
$\beta_{\gamma-\gamma_{-1}}$	0.091	0.083	0.220	0.061	0.698	-0.011	-0.057	-0.025	0.142	-0.013	1.055	0.798	0.010	0.148
	(0.218)	(0.134)	(0.318)	(0.238)	(0.464)	(0.087)	(0.175)	(0.098)	(0.135)	(0.204)	(0.182)	(0.308)	(0.119)	(0.109)
N	104	104	136	136	136	136	136	136	104	104	104	104	720	720
R^2	0.014	0.738	0.538	0.915	0.588	0.931	0.866	0.965	0.638	0.810	0.795	0.954	0.438	0.915
RMSE	0.636	0.289	0.257	0.120	0.231	0.099	0.147	0.077	0.407	0.302	0.359	0.184	0.480	0.196
Constant	YES	NO	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	NO	YES

The table presents regression results of the dispersion of (log) MRP for each input on TFPR components variation by country. Variables are recovered using the factor shares approach. Specification (1) refers to the simple linear model (21) and Specification (2) refers to the model with industry and year fixed effects (22). In both models, the observations are weighted by the industry average revenue share of total annual manufacturing revenue. Reported are the estimates for the component-specific slope coefficients ($\beta_{\gamma_{-1}}$, $\beta_{\gamma-\gamma_{-1}}$), number of observations (N), unadjusted R^2, and root mean squared error (RMSE). Standard errors computed using clustered non-parametric bootstrap over 500 repetitions are in parentheses. For the pooled regression, I use country-sector and country-year fixed effects, and the weights are normalized to sum to unity by year.

Again, caution is necessary when interpreting the regression coefficients for labor and materials. A structural assumption of the FS approach is that these inputs are allocated with perfect information of contemporaneous productivity, which is inconsistent with our decomposition of TFPR into observed and shock components for these inputs. However, if one overlooks this point, it appears that the FS approach tends to overestimate the sensitivity of inputs' MRP dispersion to observed productivity heterogeneity and underestimate the sensitivity to TFPR shocks.

Measurement error may explain the discrepancy between the two approaches. As shown, the FS approach overestimates the share of TFPR variance attributed to productivity heterogeneity observed by the firm and underestimates the share attributed to productivity shocks, compared to the baseline-GNR approach. These differences likely affect the relative weight of the two components in relation to MRP dispersion, thereby biasing the regression coefficient and the quantification of elasticities.

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. This study confirms the established relationship between productivity heterogeneity, uncertainty, and capital misallocation found in the literature. Additionally, it demonstrates that the strength of this relationship varies based on the decomposition between

However, our specifications differ. Instead of regressing standard deviations on standard deviations, I regress the log of the variances. Moreover, I control for the variance of past TFPR and the correlation between past TFPR and productivity shocks. Finally, I also include industry fixed effects.

productivity observed by the firm and productivity shocks, as well as the timing of these shocks. Furthermore, I show that the relationship generalizes heterogeneously to all inputs. Comparing the baseline results to those obtained using the FS approach highlights the limitations of the latter in studying the effects of productivity evolution.

This study reveals a positive association between MRP dispersion and TFPR variability for all inputs and demonstrates that productivity shocks primarily drive MRP dispersion, meaning that productivity idiosyncrasies are significantly linked to input misallocation among firms. This underscores the importance of considering detailed productivity dynamics to understand input misallocation. While some productivity uncertainty is unavoidable, policies that promote stability and efficiency can help mitigate misallocation. Moreover, my results suggest that accurately accounting for productivity heterogeneity and uncertainty is crucial to precisely quantify the effects of other distortions on input misallocation.

The framework in this paper has some limitations that present opportunities for future research. I showed that cross-firm variation in productivity levels is relatively small and has a lower effect on MRP dispersion compared to productivity shocks, which result from information frictions. However, heterogeneous observed productivity can still indirectly drive misallocation through correlated distortions like firing costs and financial frictions. More data are needed to disentangle MRP dispersion due to pure firm heterogeneity from that due to correlated frictions.

I believe that balancing this partial equilibrium approach with modeling specific policies or misallocation drivers, such as taxes, subsidies, and financial and allocative frictions, is a crucial next step. By examining these mechanisms, we can better understand the relative roles of distortions in generating MRP dispersion for all inputs. This will lead to improved measurement of input misallocation and a clearer assessment of the impact of mitigating policies. Ultimately, this can inform more effective policy responses.

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