Productivity Dispersions:
Could it simply be technology choice?*

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Abstract

We ask whether differences in micro-level factor productivities should be understood as a result of frictions in technology choice. Using plant and firm-level data from Chile, Colombia, Germany, and Indonesia, we document that the bulk of all productivity differences is persistent even within industries and related to highly persistent differences in the capital-labor ratio. This suggests a cost of adjusting this ratio. In fact, a model with such friction in technology choice can explain our findings not only qualitatively, but also quantitatively. At the same time, the loss in productive efficiency from this friction is modest in the sense that eliminating it would increase aggregate productivity by 3-5%.

Keywords: Productivity, Putty-clay, Heterogeneous plants.
JEL Classification Numbers: D2, E2, L1, O3, O4.

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1 Introduction

The allocation of factors to their most productive use is often seen as one of the key determinants of economic prosperity (Foster et al., 2008). While first-best efficiency requires that factors produce the same marginal revenue across all production units, many studies show this condition to be violated in micro data: factor productivities differ substantially within industries.[1]

We ask whether these micro-level differences can be understood as a result of frictions in technology choice; a setup, where firms may in principle choose from a broad set of technologies, but it is costly to search for them, to install them, and to acquire the know-how necessary to use them. This leads firms to operate one single technology which they adjust only occasionally. In between adjustments, production technology is Leontief. In particular, the capital-labor ratio, the capital intensity, remains fixed. As the economic environment changes and firms asynchronously adapt their technology in response, cross-sectional differences in factor productivities and capital intensity emerge.

This, however, is not the only empirical implication of frictional technology choice. Across all firms, differences in factor productivities and capital intensity should be predominantly long-lived. Moreover, there must be a trade-off involved. Firms with persistently high productivity in one factor should have a persistently low productivity in another factor. Further, as long as capital intensity is fixed, i.e. in the short run, labor and capital productivity can only move in the same direction. Finally, the extent of competition limits the scope of technologies used in the economy. The more competitive the environment, the larger is the pressure to abandon particularly cost-inefficient technologies.

To explore whether these implications are borne out empirically, we compute micro-level labor and capital productivity controlling for industry and time effects, and decompose them into their persistent and transitory components. To have a broad empirical base, we exploit micro data from Germany (firm-level), Chile, Colombia, and Indonesia (plant-level). Between 61% and 94% of the cross-sectional variance in labor and capital productivity is explained by their persistent components. The result is even stronger for capital intensity where the fraction explained by the persistent component is above 77% for all countries. Furthermore, the persistent components of labor and capital productivity are negatively correlated, while their transitory components are positively correlated. In addition, persistent differences in capital intensity are less dispersed in more compet-

[1] See Restuccia and Rogerson (2008), Hsieh and Klenow (2009), Peters (2013), Asker et al. (2014), Gopinath et al. (2015), and Restuccia and Santaeulalia-Llopis (2015) to name a few.

itive environments, i.e. where markups are persistently lower. Firms/plants in the most competitive quintile exhibit a 30-50% lower variance of capital intensity than those in the least competitive quintile. In summary, the data qualitatively supports the idea of a friction in technology choice driving productivity dispersions.

Next we show that this friction is also able to explain our micro-data findings quantitatively. For this purpose, we develop a dynamic partial-equilibrium model which we calibrate to aggregate targets.

Firms in our model operate a single plant, are subject to monopolistic competition, face exogenous fluctuations in relative factor prices, and frictions in technology choice in the spirit of Kaboski (2005). Upon costly adjustment, firms can choose from a broad set of technologies described by a long-run production function with constant elasticity of substitution (CES) and constant returns to scale (CRS). This choice pins down a capital intensity, which remains fixed until next adjustment, but apart from that firms can freely choose scale, so that the short-run production function is Leontief.

In the calibration of this model, there are two key elements aggregate data needs to pin down: the process for relative factor prices and the elasticity of substitution in the long-run production function. For the former, we target the time series behavior of the aggregate labor income share instead of direct measures of the relative factor price. The labor share immediately accounts for trends in labor augmenting technological change and long time series are available in National Accounts. For the elasticity of substitution, we face the problem that a regression of aggregate capital intensities on relative factor prices no longer directly identifies the long-run elasticity of substitution, unlike in the frictionless case. It rather identifies a short-run response of the economy. Still it allows us to indirectly identify our parameter of interest.

The calibrated model enables us to assess the losses in efficiency and welfare that arise from the friction in technology choice. We find that they amount to 3% of productivity and 8% of social welfare. Moreover, we show that less stable relative factor prices are able to explain the more dispersed productivities in the three developing economies. A higher volatility of relative factor prices may result from more volatile tax rates, swings in union power, and shocks to financial markets or real exchange rates. In other words, a less stable economic environment, as for example in Indonesia, increases misallocation and the implied welfare losses by more than 50%.

Despite the strong relative differences across countries, our estimated efficiency losses from misallocation are small compared to the literature. Important for this is our focus on productive efficiency, i.e. deviations from optimal capital intensity. In contrast, studies like Hsieh and Klenow (2009) have taken a broader focus including allocative efficiency, i.e. deviations from optimal scale. We disregard those deviations, showing up as dispersions in markups, for our efficiency calculations for two reasons. First, these dispersions might reflect efficient differentiation within industry. For example, they might stem from alternative strategies on product quality or range (e.g. Bar-Isaac et al., 2012), think of generics vs. patented pharmaceuticals. Second, there is already a broad set of theories predicting markup dispersions to which we have little to add. Think models with price setting frictions á la Calvo (1983), with building a customer base (Gourio and Rudanko, 2014), or with entry dynamics and innovation as in Peters (2013). All of these provide explanations of productivity dispersions through heterogeneous markups as endogenous objects. At the same time, our data suggests that markup dispersions themselves explain only a minority of all productivity dispersion.

In other words, the friction that explains productivity dispersions needs to produce differences in capital intensities. Capital adjustment costs in general are such friction (see Asker et al., 2014). Yet, we show that capital adjustment frictions produce too large transitory and too small persistent differences in capital intensity. The reason is that firms respond to short-run shocks by strongly varying their capital intensity if labor is much more flexible than capital.[2]

Hence to match the data, it is necessary to assume relatively rigid capital intensities in the short-run. This links our paper to the traditional putty-clay assumption (Johansen, 1959), which has been advocated to address a broad array of other empirical phenomena (Gilchrist and Williams, 2000, 2005; Gourio, 2011). Particularly closely related is Kaboski's (2005) model of putty-clay technology choice under factor price uncertainty. An important insight from this paper that carries over to our setup is that firms underreact to current prices in setting their technology, such that the regression techniques usually used to identify the long-run elasticity of substitution (see e.g. Raval (2014) or Oberfield and Raval (2014) for recent contributions or Chirinko (2008) for an overview) are subject to a downwards bias. In fact, we show that this downwards bias is likely substantial. Our baseline of the long-run elasticity of substitution is about five, while the aggregate short-run elasticity being 0.75. This high elasticity not only has important implications for income-shares (see e.g. Solow, 1956; Piketty, 2011, 2014; Karabarbounis and Neiman, 2013) but is also key to obtain small productive efficiency losses from dispersions in capital intensities.

The remainder of this paper is organized as follows: Section 2 describes our tech-

[2] We conjecture that similar issues are encountered by alternative theories generating productivity dispersions through endogeneous firm-specific shadow-prices of capital, such as through financial frictions (Amaral and Quintin, 2010; Banerjee and Moll, 2010; Buera et al., 2011; Midrigan and Xu, 2013; Moll, 2014), imperfect information (David et al., 2013), or contractual incompleteness (Acemoglu et al., 2007).

nology choice model in a simplified two-period setup. This allows us to derive the main qualitative insights that we have sketched in this Introduction and guides our empirical analysis in Section 3. Section 4 then presents our dynamic model, followed by the quantitative results in Section 5. Section 6 compares to an alternative specification of capital adjustment costs instead of a friction in technology choice and Section 7 concludes. An Appendix follows.

2 Two-Period Model of Technology Choice

To guide our empirical analysis we start off with a two-period version of our technology choice model. Assume a mass of firms of measure one. Each firm, i, is endowed with one plant that has an exogenously given capital intensity $k_i = \frac{K_i}{N_i}$, where K_i is the physical amount of capital and N_i is labor. We assume that wages, W, and user costs of capital, R, are exogenously given, but stochastic.

2.1 Output choice

Each firm has a constant returns to scale production technology and faces monopolistic competition for its product, where the elasticity, ξ_i, of demand for the product, y_i, of firm i is firm-specific and constant, such that prices are given by

$$p_i = \frac{1}{1-\xi_i} z_i^{\xi_i} y_i^{-\xi_i},$$

where z_i is the stochastic market size for firm i's product. Unit costs of production depend on the plant's capital intensity and factor prices, $c_i = c(k_i, W, R)$. The firm maximizes profits, and we assume that the firm needs to decide about output before knowing actual factor prices and demand. The optimal policy will choose output in order to stabilize the expected markup at its optimal level. The expected gross markup is constant, $\frac{1}{1-\xi_i} > 1$. Denoting the expectations operator as $\mathbb{E}$, it is straightforward to show that the profit maximizing output, y_i^* and *expected* profits under the optimal policy, π^*, are given by

$$y_i^* = \left[\frac{\mathbb{E}z_i^{\xi_i}}{\mathbb{E}c(k_i, R, W)}\right]^{1/\xi_i}; \qquad \pi_i^* = \frac{\xi_i}{1-\xi_i} y_i^* \mathbb{E}c(k_i, R, W). \tag{1}$$

2.2 Revenue productivities

This implies that firms facing higher demand elasticities, ξ_i, have on average larger markups and larger revenue factor productivities. Deviations from expected costs, $\mathbb{E}c_i/c_i$, and deviations from expected demand, $z_i^{\xi_i}/\mathbb{E}z_i^{\xi_i}$, lead to additional fluctuations in realized markups, given by:

$$\frac{p_i y_i^*}{WN_i + Rk_iN_i} = \frac{1}{1-\xi_i}\frac{z_i^{\xi_i}}{\mathbb{E}z_i^{\xi_i}}\frac{\mathbb{E}c_i}{c_i}. \tag{2}$$

Similarly, splitting up this term in two components, these fluctuations move the capital and labor expenses per value added:

$$\frac{p_i y_i^*}{WN_i} = \frac{1}{1-\xi_i}\frac{z_i^{\xi_i}}{\mathbb{E}z_i^{\xi_i}}\frac{\mathbb{E}(W+Rk_i)}{W} \tag{3}$$

$$\frac{p_i y_i^*}{Rk_iN_i} = \frac{1}{1-\xi_i}\frac{z_i^{\xi_i}}{\mathbb{E}z_i^{\xi_i}}\frac{\mathbb{E}(W+Rk_i)}{Rk_i} \tag{4}$$

On the one hand, (3) and (4) show that firms with higher (target) markups, $\frac{1}{1-\xi_i}$ exhibit both higher labor and capital productivities. Similarly, positive and unforeseen demand shocks, $z_i^{\xi_i}/\mathbb{E}z_i^{\xi_i}$, increase both factor productivities. Importantly, in a more general multi-period setup, these deviations from expectations could only be transitory. On the other hand, firms with higher capital intensity have a lower capital and higher labor revenue-productivity, even when these capital intensity differences are expected.

To summarize, productivities differ across firms either because of differences in size relative to demand (the first two terms) or due to differences in capital intensity and factor prices (the last term) in (3) and (4).[3]

2.3 Choice of technology

We assume that in the period preceding production, the firm can opt to replace its existing plant, setting up a new one with different capital intensity k. In doing so, the firm compares expected profits with and without technology adjustment to decide the period preceding production whether to produce with its initially given capital intensity or to invest in changing the technology. We assume adjustment is costly as it disrupts production. This disruption summarizes all costs of searching for a technology, installing

[3] As evident from equation 2, in this environment, adding an additional shock to unit costs (a TFP shock) has the same implications as a demand shock.

it and learning to operate it. Upon adjustment the firm forgoes a fraction ϕ_i of next period's profits, where ϕ_i stochastic and drawn from a distribution Φ. The firm draws ϕ_i before it decides about adjustment and hence adjusts capital intensity to $\hat{k}$, the capital intensity that minimizes expected unit costs, whenever

$$(1-\phi_i)E\pi(\hat{k}) > E\pi(k_i).$$

This simplifies to

$$(1-\phi_i) > \left(\frac{\mathbb{E}c(k_i,R,W)}{\mathbb{E}c(\hat{k},R,W)}\right)^{\frac{\xi_i-1}{\xi_i}}, \tag{5}$$

using the expressions in (1) for expected profits.

Since $\frac{\mathbb{E}c(k_i,R,W)}{\mathbb{E}c(\hat{k},R,W)} \geq 1$, firms with higher elasticity of demand, ξ_i, are less likely to adjust for a given ex ante capital intensity k_i. The reason is that firms with high market power can offload their higher unit costs to consumers and hence have less incentive to invest in efficient capital intensities. This is reminiscent of Leibenstein's (1966) X-inefficiency of monopolies or Bester and Petrakis's (1993) results for oligopolies.[4]

As a result, ex-post capital-intensity will be less dispersed within the group of firms with low markups than among high-markup firms if the ex-ante distribution of capital intensities is centered around the cost minimizing level $\hat{k}$.

2.4 Unit costs

To specify more concretely the relation between capital intensity and unit costs, we assume that the long-run technology is given by a constant elasticity of substitution (CES) production function with substitution elasticity σ, such that the output of a plant with capital intensity k_i is given by

$$y_i = \left[\alpha k_i^{\frac{\sigma-1}{\sigma}} + (1-\alpha)A^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} N_i, \tag{6}$$

where A captures (Harrod neutral) labor-augmenting technological change, and α is the distribution parameter.

This implies that *realized* unit costs, $c_i = \frac{Rk_iN_i+WN_i}{y_i}$ are minimal at capital intensity

[4]There is, however, one interesting side result of our setup. One can easily show that under the specific assumption of an isoelastic demand curve and monopolistic competition, producer profits and consumer rents are equal and therefore, total social surplus of adjustment as well as the social costs of adjustment need to be scaled by factor two such that the individual optimal adjustment choice is socially optimal.

k^*, given by

$$k^* = \left[\frac{\alpha}{1-\alpha}\frac{W}{R}\right]^{\sigma} A^{1-\sigma}. \tag{7}$$

Now, to obtain an expression that allows us to relate the cross-sectional average unit costs to the first two moments of the capital intensity distribution, we use a log second-order approximation around that minimum:

$$\mathbb{E}^x\left[\log\frac{c(k_i,R,W)}{c(k^*,R,W)}\right] \approx \frac{1}{2\sigma}s^*(1-s^*)\left\{\left[\mathbb{E}^x\left(\log\frac{k_i}{k^*}\right)\right]^2 + \mathbb{V}^x(\log k_i)\right\}, \tag{8}$$

where s^* is the capital expenditure share in the cost-minimizing optimum[5]

$$s^* = Rk^*/(W+Rk^*),$$

and $\mathbb{E}^x$ denotes the cross-sectional average and $\mathbb{V}^x$ the cross-sectional variance. In words, the efficiency loss is composed of the average relative difference of capital intensity from its optimum, $\mathbb{E}^x\log(k_i/k^*)$, and the cross-sectional dispersion of capital intensity across plants, $\mathbb{V}^x(\log k_i)$. Importantly, the higher the elasticity of substitution between labor and capital, σ, the lower the efficiency loss from not re-setting capital intensities to their optimum.

3 Empirics

3.1 Data description

We document factor productivity and capital intensity dispersion in firm-level data from Germany, and plant-level data from Chile, Colombia and Indonesia. For Germany, we use the balance sheet data base of the Bundesbank, USTAN, which is a private sector, annual firm-level data available for 26 years (1973-1998).[6] For Chile, Colombia and Indonesia, we have plant level data from the ENIA survey for 1995-2007, the EAM census for 1977-1991 and the IBS dataset for 1988-2010, respectively. These datasets are focused on the manufacturing sector, with the exception of Germany, which provides information for the entire private non-financial business sector.[7]

When preparing the data for our analysis, we make sure to treat them in the most

[5] See Appendix B for details.

[6] See Bachmann and Bayer (2014) for a detailed description.

[7] In particular, private non-financial business sector includes Agriculture, Energy and Mining, Manufacturing, Construction, and Trade.

comparable way. From each survey, we use a firm's/plant's four-digit industry code, wage bill, value-added and book or current value of capital stock. In order to obtain economically consistent capital series for each firm/plant, we re-calculate capital stocks using the perpetual inventory method when the data set does not include estimates of the capital stock at current values. When recalculating the capital stock, we exploit information of capital disaggregated into structures and equipment, which allows us to control for heterogeneity in capital composition across plants.

Our capital productivity measure requires information on the real interest rate and economic depreciation. For the latter, we do not rely on the depreciation reported by plants, that is potentially biased for tax purposes or other reasons, but instead use economic depreciation rates obtained from National Statistics or external studies if the former is not available and take the different capital good mixes across firms/plants into account. Since it is hard to identify the right measure for a real rate for the developing economies, we instead fix the real rate to 5% for all economies. This implies user costs of capital $R_{it} = 5\% + \delta_{it}$.[8] In generating cross-sectional statistics, time variations in user costs are controlled for by taking out four-digit industry-year fixed effects. The data treatment and sample selection is described in detail in Appendix A.2.

3.2 Productivities and their transitory and persistent component

We compute average factor productivities for capital and labor per firm and year using the reported value added per firm/plant at current prices, $p_{it}y_{it}$, labor expenses, $W_t N_{it}$ as reported in the profit and loss statements, and imputed capital expenses, $R_{it}K_{it}$. Taking logs, we define revenue productivities of labor and capital

$$\alpha_{it}^N := \log(p_{it}y_{it}) - \log(W_t N_{it}); \qquad \alpha_{it}^K := \log(p_{it}y_{it}) - \log(R_{it}K_{it}). \tag{9}$$

Using expenditures and value added implicitly controls for quality differences in both inputs and outputs (c.f. Hsieh and Klenow, 2009). In addition, we construct markups as value added relative to total expenditures on labor and capital

$$mc_{it} := \log(p_{it}y_{it}) - \log(R_{it}K_{it} + W_t N_{it}). \tag{10}$$

[8]The economic depreciation rate of equipment and structures for Germany is obtained from *Volkswirtschaftliche Gesamtrechnung* (VGR) while for Chile we obtain time series from Henriquez (2008). Finally, as for Colombia and Indonesia, we consider the average depreciation in Chile for the available period given the absence of national data sources. The depreciation rate values are 15.1% (equipment) and 3.3% (structures) in Germany, while they are on average 10.5% (equipment) and 4.4% (structures) for the rest of the countries.

Table 1: Transitory and persistent components of factor productivities

	$\text{std}(\hat{\alpha}_{it}^L)$	$\text{std}(\hat{\alpha}_{it}^K)$	$\rho(\hat{\alpha}_{it}^L, \hat{\alpha}_{it}^K)$	$\text{std}(\bar{\alpha}_{it}^L)$	$\text{std}(\bar{\alpha}_{it}^K)$	$\rho(\bar{\alpha}_{it}^L, \bar{\alpha}_{it}^K)$
	Transitory Component			Persistent Component		
DE	0.066	0.119	0.352	0.229	0.456	-0.207
	(0.000)	(0.001)	(0.002)	(0.002)	(0.004)	(0.004)
CL	0.184	0.281	0.449	0.232	0.577	-0.190
	(0.006)	(0.008)	(0.017)	(0.009)	(0.028)	(0.021)
CO	0.144	0.172	0.517	0.257	0.568	-0.234
	(0.003)	(0.004)	(0.012)	(0.008)	(0.023)	(0.018)
ID	0.211	0.369	0.343	0.255	0.669	-0.269
	(0.003)	(0.005)	(0.007)	(0.004)	(0.013)	(0.009)

Notes: Cross-sectional standard-deviations (std) and correlation (ρ) of transitory and persistent components of labor- and capital productivity, α_{it}^L and α_{it}^K as in (9). DE: Germany, CL: Chile, CO: Colombia, ID: Indonesia. Transitory and persistent components are obtained by applying a five year moving average filter. Factor productivities are demeaned by 4-digit industry and year, and expressed in logs. In parentheses: Clustered standard errors at the firm/plant level.

Finally, we calculate the price weighted capital intensity,

$$\kappa_{it} = \log(R_{it}K_{it}) - \log(W_t N_{it}). \tag{11}$$

For any of these variables, say x_{it}, we calculate 5-year moving averages, denoted $\bar{x}_{it} := \frac{1}{5}\sum_{s=-2}^{2} x_{it+s}$, to identify the persistent component and deviations thereof, $\hat{x}_{it} = x_{it} - \bar{x}_{it}$, to identify the transitory component.

We then take out four-digit industry-year fixed effects and calculate dispersions and correlations between the factor productivities for each component.

3.3 Empirical findings

Table 1 reports standard deviations and correlation for labor and capital productivity and for all four countries. Three observations stand out: First, capital and labor productivity are positively correlated in the transitory component ($\rho \approx 40\%$) while they are negatively correlated in the persistent component ($\rho \approx -20\%$). Using the expressions for factor productivities in Section 2, see (3) and (4), deviations from optimal size are more important in the short run, while deviations from optimal capital intensity are more important in explaining long-run productivity differences. Second, the persistent components in productivity explain the vast majority of cross-sectional productivity differences (between 60% and 92% for labor and between 79% and 94% for capital). Third, the developing economies show larger productivity dispersions.

As the positive/negative correlation pattern between labor and capital productivity is a particularly important prediction of technology choice, we check whether this pattern holds within the four-digit industries. Figure 1 shows that this is the case for the vast majority of industries.

In light of our results in Section 2, it is useful to look at markup and capital intensity differences, see Table 2. In particular, (8) allows us to relate the latter directly to increases in unit costs. For all countries, differences in capital intensity are very persistent. The transitory component makes up only between 4% (Germany) and 17% (Indonesia) of the total variance. At the same time, persistent differences in capital intensity are substantially more dispersed in Chile, Colombia, and Indonesia than they are in Germany with variances being twice as high in Indonesia than in Germany.

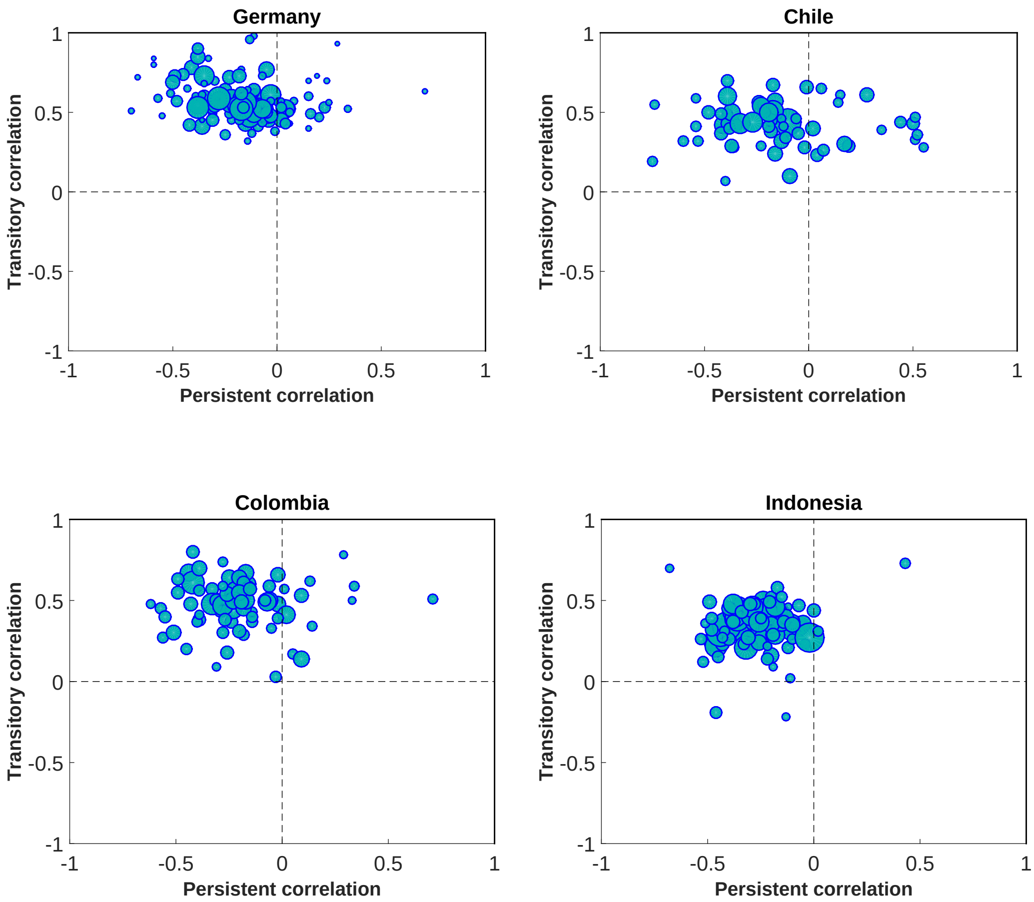
On the contrary, the dispersion of persistent cross-sectional markup differences is strikingly similar across countries, and transitory differences in markups are an important component of the total cross-sectional variance of markups – at least in the developing economies (30% in Colombia, 50% in Chile and Indonesia) but less so in Germany (12%).[9]

These results along with (3) and (4) suggest that an important component in the persistent differences in productivity is the choice of capital intensities; deviations in optimal scale being important but minor.

Using the log approximation in (8), the numbers in Table 2 imply, an increase of unit-costs between 3.3% for Germany and 6.5% for Indonesia compared to the frictionless minimum. These numbers assume a unit long-run elasticity of substitution and a capital share of one third, which yields as cost increase $\mathbb{V}(\kappa)/9$, ignoring potential differences in average and static-optimal capital intensities. Note also that these numbers for the cost increase highly depend on the assumed substitution elasticity and to an important but lesser extent on the capital share. Decreasing the substitution elasticity to one half doubles the efficiency loss all else equal. Lowering the capital share to one fifth (e.g. to account for pure profits) instead decreases the efficiency loss by roughly one third.

[9]This might relate to the fact that demand is less stable in the developing economies. In fact, the cross-sectional standard deviation of value-added growth is two to four times larger in these economies than in Germany.

Figure 1: Correlations of factor productivities by four-digit industry



Notes: *Transitory (Persistent) Correlation*: Correlation between the transitory (persistent) component of labor and capital productivity at the firm/plant level, controlling for time-fixed effects. Each circle represents a four digit industry, where the size of a circle reflects aggregate employment in that industry. For this figure, we restrict industries to include at least 20 firms/plants. The number of industries inside the upper-left quadrant is 99 (out of 125) in Germany, 45 (out of 61) in Chile, 62 (out of 73) in Colombia, and 85 (out of 90) in Indonesia.

Table 2: Transitory and persistent components of markup and capital intensity

	$\text{std}(\hat{mc}_{it})$	$\text{std}(\hat{\kappa}_{it})$	$\rho(\hat{mc}_{it}, \hat{\kappa}_{it})$	$\text{std}(\bar{mc}_{it})$	$\text{std}(\bar{\kappa}_{it})$	$\rho(\bar{mc}^{L}_{it}, \bar{\kappa}_{it})$
	Transitory Component			Persistent Component		
DE	0.064	0.114	-0.155	0.172	0.551	0.062
	(0.000)	(0.001)	(0.002)	(0.001)	(0.004)	(0.004)
CL	0.177	0.258	-0.090	0.184	0.661	-0.085
	(0.005)	(0.009)	(0.017)	(0.005)	(0.029)	(0.022)
CO	0.134	0.157	-0.016	0.206	0.676	-0.232
	(0.003)	(0.004)	(0.012)	(0.005)	(0.025)	(0.018)
ID	0.203	0.357	-0.120	0.195	0.778	-0.021
	(0.002)	(0.005)	(0.007)	(0.003)	(0.014)	(0.010)

Notes: Capital intensities, κ_{it}, and markups, mc_{it}, as defined in (10) and (11). See notes of Table 1 for further explanation.

To understand to what extent firms actively take these unit cost increases into account, we split the sample according to firm/plant characteristics – age, size, and importantly a firm's average markup – and compute again the dispersions of the persistent component of capital intensity, see Table 3. While there are some differences in these dispersions according to age and size, these are neither large nor systematic. What stands out is splitting the sample according to the average markup. The highest markup quintile exhibits between 30% and 60% higher capital intensity dispersions (in terms of variances) than the lowest markup quintile. This is in line with the qualitative predictions of our model.

In Appendix A.5, we show that our empirical findings are robust to alternative ways of decomposing into transitory and persistent components, and to alternative measures of dispersion and correlation. We also find that persistent capital intensity differences are more dispersed for high-markup firms/plants even when controlling for size and age.

Table 3: Persistent component of capital intensity by firm/plant characteristics

	std($\bar{\kappa_{it}}$)					
	Markups		Size		Age	
	Bottom Quintile	Top Quintile	Bottom Quintile	Top Quintile	Young	Old
DE	0.545 (0.010)	0.622 (0.010)	0.610 (0.009)	0.509 (0.011)	n.a.	n.a.
CL	0.568 (0.042)	0.713 (0.075)	0.749 (0.068)	0.622 (0.058)	n.a.	n.a.
CO	0.547 (0.035)	0.694 (0.061)	0.763 (0.051)	0.669 (0.061)	0.697 (0.100)	0.699 (0.048)
ID	0.716 (0.028)	0.834 (0.035)	0.830 (0.034)	0.816 (0.035)	0.770 (0.058)	0.801 (0.038)

Notes: Bottom (top) markup quintile: firm/plant average markup below the 20th percentile (above the 80th percentile). Old (young): Plant age below 4 years (above 15 years). Bottom (top) size quintile: firm/plant average employment below the 20th percentile (above 80th percentile). The micro data from Germany and Chile does not include age. See notes of Table 1 and 2 for further explanation.

4 Dynamic Model of Technology Choice

As the qualitative predictions of our simple two-period model of technology choice are in line with the empirical findings, we explore next whether the model is also quantitatively able to produce the observed dispersions. This allows us to assess the welfare costs arising from a friction in technology choice, too.

4.1 The choice of capital intensity

We remain within the basic setup of our two-period model. Every period, a firm produces a predetermined output with a given capital intensity, then decides whether to adjust technology, closing the existing plant and opening a new one, and finally sets the quantity it wants to produce and sell next period. In case of technology adjustment, production is disrupted for a fraction ϕ of a period. We assume ϕ to be i.i.d. with cumulative distribution function Φ.[10]

For simplicity, we model all movements of factor prices as changes in the real wage rate, keeping interest rates constant. We assume a trend growth of the relative wage and labor productivity, such that we can formulate the model around this trend. This means, the capital intensity of non-adjusters decreases by a constant factor every period, denoted by γ.

Along the trend, we assume stochastic fluctuations for the decisive relative factor costs W_t/R_t, which follows a Gaussian AR-1 process in logs

$$\omega_t = \log\left(\frac{W_t}{R_t}\right) = (1-\rho_\omega)\bar{\omega} + \rho_\omega \omega_{t-1} + \epsilon_t^\omega \qquad \epsilon_t^\omega \sim \mathcal{N}(0, (1-\rho_\omega^2)\sigma_\omega^2,$$

where $\rho_\omega \in (0,1)$. Similarly, a firm's market size z_{it} evolves as

$$\log z_{it} = (1-\rho_z)\mu_z + \rho_z \log z_{it-1} + \epsilon_t^z, \qquad \epsilon_t^z \sim \mathcal{N}(0, (1-\rho_z^2)\sigma_z^2),$$

where $\rho_z \in (0,1)$. As in Section 2, we assume a firm knows only current market size z and prices ω as well as the fraction ϕ of next period's profit lost in case of adjustment, when making the decision to adjust technology for the next period. Under these assumptions, the expected continuation value of a firm that decides to adjust is given by

$$v^a(\phi, z, \omega) = \max_{k'} \Big\{(1-\phi)\pi^*(k', z, \omega) + \beta \mathbb{E}_{z',\omega'}[v(k', z', \omega')]\Big\}, \tag{12}$$

while the continuation value for a non-adjuster is

$$v^n(k, z, \omega) = \pi^*((1-\gamma)k, z, \omega) + \beta \mathbb{E}_{z',\omega'}[v((1-\gamma)k, z', \omega')]. \tag{13}$$

In both cases, expected next period's profits, $\pi^*(k, z, \omega)$, are as given in (1) and $\beta = \frac{1}{1+r}$ is the discount factor and r is the risk-free real rate.

The expected future value of a firm before knowing adjustment costs, $\mathbb{E}_{z',\omega'}[v]$, is given by the upper envelope of v^a and v^n integrating out i.i.d. adjustment costs and shocks to market size and factor prices

$$\mathbb{E}_{z',\omega'}[v(k, z', \omega')] = \mathbb{E}_{\phi',z',\omega'}\left[\max\left\{v^a(\phi', z', \omega'), v^n(k, z', \omega')\right\}\right]. \tag{14}$$

Appendix C shows that the solution to (1), (12), (13), and (14) exists and is unique.

[10]This i.i.d. assumption follows the literature on lumpy capital adjustment.

4.2 Optimal firm policies

The optimal policy is to adjust capital intensity whenever $\phi < \bar{\phi}(k, z, \omega)$, with the threshold adjustment cost $\bar{\phi}(k, z, \omega)$ defined by $v^a[\bar{\phi}(k, z, \omega), z, \omega] = v^n(k, z, \omega)$. Conditional on adjustment, the optimal new capital intensity is

$$\hat{k}(\phi, z, \omega) = \arg\max_{k'} \Big\{ (1-\phi)\pi^*(k', z, \omega) + \mathbb{E}_{z',\omega'}[v(k', z', \omega')] \Big\}.$$

To understand the quantitative results and the calibration strategy, it is useful to compare the dynamically optimal capital intensity $\hat{k}$ with the statically optimal one k^*. Figure 2 displays the adjustment probability $\Phi(\bar{\phi})$, the capital intensity choice $\hat{k}$ for a a low and high markup firm, and the statically optimal capital intensity k^*.

A firm will never adjust when current capital intensity and its dynamic target coincide. Left and right of this point on the capital-intensity line, adjustment probabilities are increasing, see Figure 2(a). As in the two-period setup, firms with high average markups adjust their capital intensity less often than firms facing elastic prices.

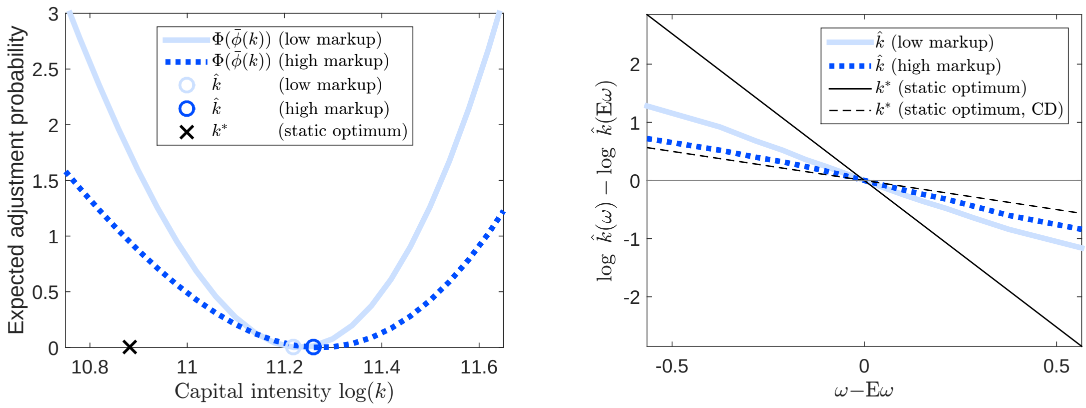
What is new in the dynamic setup is that market power changes a firm's policy regarding the intensive margin policies, too. This policy can be intuitively thought of as minimizing the average distance of the statically optimal and the realized capital intensity between two adjustments. This has three implications: First, upon adjustment, firms will overshoot the statically optimal capital intensity k_t^* to compensate for the aggregate trend γ. Second, the dynamically optimal target reacts less to changes in ω_t than k_t^* because of mean reversion in ω_t. Third, as high-markup firms wait longer until readjustment both overshooting – see Figure 2 (a) – and underreaction – see Figure 2 (b) – is stronger for firms with more market power.

4.3 Aggregate capital intensity and relative factor prices

Underreaction now has important consequences for the relation of the aggregate capital intensity and relative factor prices. In a static setup, a regression of the aggregate capital intensity on the contemporaneous relative factor price ω identifies the long-run elasticity of substitution σ, see (7). In our frictional dynamic setup, this is no longer the case.

The estimated regression coefficient, $\hat{\sigma}$, will only recover an average correlation, which we refer to as aggregate short-run elasticity of substitution. This will be an average of how current relative factor prices ω_t correlate with the various technology vintages of age s, $\hat{k}_{t-s}$, weighted by their share in the economy Γ_s.

Figure 2: Technology adjustment policy



(a) extensive margin

(b) intensive margin

Notes: Subfigure (a) shows the adjustment probabilities, subfigure (b), the chosen capital intensity conditional on adjustment. The policies are obtained using the parameters of our baseline calibration, see Section 5. For illustrative purposes, we fix (z) and (k) to their average values and compare firms in the lowest and highest markup quintile. In subfigure (b), policies are expressed as deviations from its value at mean relative factor price.

Expressed formally,[11] the estimated $\hat{\sigma}$ in the dynamic model is

$$\hat{\sigma} \approx \mathbb{E} \sum_{s=0}^{\infty} \Gamma_s \frac{\partial \hat{k}_{t-s}}{\partial \omega_{t-s}} corr(\omega_{t-s}, \omega_t). \tag{15}$$

This estimated coefficient will be substantially smaller than σ. First, underreaction implies that $\frac{\partial \hat{k}_t}{\partial \omega_t} < \sigma$. Second, old vintages only covary with ω_t to the extent that factor prices are persistent, and $corr(\omega_t, \omega_{t-s}) = \rho_\omega^s < 1$.

In fact, the difference between the short-run elasticity, $\hat{\sigma}$, and its long-run counterpart, σ, can be large as the following example shows. Suppose a firm adjusts *deterministically* every S periods. To obtain a closed-form expression, we assume that a firm adjusting at time t minimizes the expected quadratic loss $\mathbb{E} \sum_{s=0}^{S} \beta^s (\log \hat{k}_t - \log k^*_{t+s})^2$ until the next adjustment. The solution to this sets $\log \hat{k}_t = \frac{1-\beta}{1-\beta^{S+1}} \sum_{s=0}^{S} \beta^s \mathbb{E} \log k^*_{t+s}$.

[11]We ignore the difference between the log of the average capital intensity and the average over vintages of log capital intensities.

Using $\log k_t^* = \sigma\omega_t + c$, with c a constant, we obtain

$$\log \hat{k} - c = \sigma \frac{1-\beta}{1-\beta^S} \sum_{s=0}^{S-1} (\beta\rho_\omega)^s (\omega_t - \bar{\omega}) = \sigma \frac{1-\beta}{1-\beta^S} \frac{1-(\beta\rho_\omega)^S}{1-\beta\rho_\omega} (\omega_t - \bar{\omega}).$$

Given $S = 10$, $\rho_\omega = 0.8$, and $\beta = 0.95$, this yields $\log k_t^* - c \approx 0.49\sigma(\omega_t - \bar{\omega})$, showing exactly the type of underreaction depicted in Figure 2, and

$$\hat{\sigma} \approx 0.49\sigma \left(\frac{1}{10} \frac{1-\rho_\omega^{10}}{1-\rho_\omega} \right) \approx 0.22\sigma,$$

which highlights the wedge between short-run and long-run elasticity of substitution. Despite the relative factor prices being persistent, the short-run elasticity underestimates the long-run elasticity by almost factor five. Even with more persistent factor prices, say $\rho_\omega = 0.9$ the two elasticities would remain different by a factor of two.

5 Quantitative Results

5.1 Calibration

Our baseline calibration is for Germany. Starting from this calibration, we ask whether less stable relative factor prices as reflected in larger fluctuations of the aggregate labor share in the developing economies can explain their larger capital intensity and factor productivity dispersions.

A first set of parameters is calibrated outside the model – those parameters that can be observed directly in the data independent of our model: the steady state growth rate of capital intensity γ and the average relative factor price $\bar{\omega}$. The latter is given by the interest rate r, which we set to 5% as in Section 3, the depreciation rate δ, taken as the average implied depreciation rate in the micro data, and the average salary per employee W from the micro data. We calibrate to annual frequency in line with the frequency of the micro data. Details on the aggregate and micro data used for and details of the calibration can be found in Appendix D.2.

Moreover, we create five groups of firms representing the empirical quintiles of the observed markups in the micro data. We set the persistence of shocks to market size z to $\rho_z = 0.9675$ in line with Bachmann and Bayer (2013) that uses the same micro data for Germany. The baseline values of parameters calibrated outside the model is reported in Table 4.

What remains to be calibrated are the parameters of the production function σ, α

Table 4: Parameters calibrated outside the model

Steady state growth rate	γ	0.04
Interest rate	r	0.05
Depreciation rate	δ	0.09
Avg. real wage (in 1,000 DM)	W	29.2
Demand shifter persistence	ρ_z	0.9675
Demand elasticity	ξ_1	0.19
(5 equally	ξ_2	0.27
large groups)	ξ_3	0.33
	ξ_4	0.38
	ξ_5	0.48

Notes: Real wage W is expressed in Deutsche Mark (1986), which equals 3/4 Euro (2005).

and A_0, the standard deviation and persistence of relative factor prices σ_ω and ρ_ω, the standard deviation and mean of the demand shifter σ_z and μ_z, as well as the adjustment cost distribution. Of course all parameters are calibrated jointly, but to guide intuition, we link each parameters to those single data moments most informative for them. We calculate all model moments as averages from the corresponding moments of 200 model simulations over 20 periods each (excluding 200 burn-in periods).

To fix μ_z we target average total costs, while σ_z is identified by the standard deviation of value added in our firm-level data. We calibrate the CES-production function parameters A_0 and α using transformed capital and labor shares as calibration targets – a method suggested by Cantore and Levine (2012).[12] We define

$$\psi_N := (1-s)\left(\frac{EX}{N}\right)^{\frac{\sigma-1}{\sigma}} \quad ; \qquad \psi_K := s\left(\frac{EX}{K}\right)^{\frac{\sigma-1}{\sigma}} \tag{16}$$

where $N = \sum_{i,t} N_{i,t}$, $K = \sum_{i,t} K_{i,t}$ are aggregate labor and capital, respectively, $EX = \sum_{i,t}(W_t N_{it} + R_t K_{it})$ is aggregate total expenditure, $s = \frac{\sum_{i,t} R_t K_{it}}{EX}$ is the aggregate share of capital in total expenditures. Notice that in a frictionless, static version of this model, ψ_N and ψ_K are invariant to relative factor prices and map directly into α and A_0 in (6).

To calibrate the factor price process, we let the model match the time series behavior of the aggregate labor share. We opt for the labor share instead of a direct measures

[12] We assume the units of measurement being the number of workers and capital measured in consumption goods expressed in a money value for a baseline year.

of factor prices to control for endogenous reactions of factor prices to shocks to factor augmenting technological change. For our calibration, we first estimate an AR-1 process for the labor share using national statistics data.[13] We use aggregate data here instead of the micro data in order to obtain a longer time series. We then replicate this estimation on simulated data and choose σ_ω and ρ_ω in order to match the empirical labor share process for Germany. We find substantial fluctuations in the German labor share that are fairly persistent, see Table 5.

These fluctuations are also closely linked to the substitution elasticity, σ, of the long-run technology. As explained in Section 4.2, a regression of the aggregate capital intensity on current factor prices no longer identifies the long-run elasticity of substitution. Still such measure of the short-run aggregate elasticity – the regression coefficient of aggregate capital intensity, $\log(\sum_i K_{it}) - \log(\sum_i N_{it})$, on relative factor prices ω_t – is informative for the long-run elasticity. We therefore calibrate σ by matching an aggregate short-run substitution elasticity of 0.75 which is mid-range of the numbers summarized in Chirinko (2008). We provide extensive robustness checks with respect to this calibration target.

Finally, we specify the adjustment cost distribution, Φ, as an exponential distribution described by distribution parameter λ_ϕ with $\mathbb{E}[\phi] = 1/\lambda_\phi$. We calibrate λ_ϕ by matching the fraction of plants older than 10 years of 56% as can be obtained from the ELFLOP data of the German Bureau of Labor (IAB), see (Bachmann et al., 2011). We provide robustness through an alternative calibration that assumes 25% of old plants have non-old technology vintages. Put differently, instead of closing a plant and opening a new, an old plant may be refurbished.

The parameters calibrated inside the model and the matched moments are summarized in Table 5. Our calibration recovers large fluctuations in relative factor prices with an unconditional standard deviation of 30% (log-scale) and a mild annual persistence of 78%. These numbers are reasonable as the persistence is in line with typical business cycle persistence and a 32% increase in relative factor costs could for example result from a typical recession event: a 10% increase in real unit labor costs and a 2 percentage point decrease in the real interest rate.

The implied long-run elasticity of substitution is 5.1 and hence much higher than the matched aggregate short-run substitution elasticity of 0.75. This has important implications both outside our model for the reaction of the labor share to permanent changes, say in factor supply (see Solow, 1956; Piketty, 2011), and as we will see inside our model for the efficiency losses from the technology friction and the interpretation of

[13]Given there is no available information on the labor share in manufacturing at Indonesia from National Statistics, we opt to construct aggregate labor share using the micro data.

Table 5: Parameters calibrated within the dynamic technology choice model

Calibration targets		Data	Model
Avg. factor expenditures (in 1,000,000 DM)		7.54	7.38
log(VA) std.		1.24	1.24
Transformed capital share, ψ_K		0.15	0.15
Transformed labor share, ψ_N		3659	3636
Aggr. labor share std. (in %)		3.30	3.30
Aggr. labor share persistence (in %)		88.1	88.8
Aggr. (short-run) substitution elasticity		0.75	0.75
Share of plants older than 10 years (in %)		56.5	56.9
Calibrated model parameters			
CES substitution elasticity	σ		5.1
CES capital weight (in %)	α		15.0
CES labor productivity (in 1,000 DM)	A_0		33.9
Relative factor price std. (in %)	σ_ω		30.1
Relative factor price persistence (in %)	ρ_ω		78.4
Demand shifter std.	σ_z		1.3
Demand shifter mean (in 1,000,000 DM)	μ_z		7.6
Avg. adjustment cost draw	$1/\lambda_\psi$		2.6

Notes: Calibration targets K/N and $WN + RK$, and parameters μ_z and A_0 are expressed in Deutsche Mark (1986), which equals 3/4 Euro (2005). The model is simulated for a set of 200 economies with each 2,000 plants and 20 years. log(VA) std.: Cross-Sectional standard deviation in the log of value added of firms.

dispersions in capital intensities.

5.2 Baseline model

Table 6 presents the cross-sectional standard deviations from the simulated model. The cross sectional dispersions are obtained as averages over 200 sets of economies where we simulate 2,000 plants for 20 years.

Overall, the model calibrated primarily to the aggregate time series behavior of the labor share fits the empirical cross-sectional data well. Note that in terms of cross-sectional moments only the dispersion of persistent markups differences has been targeted.

We obtain that the bulk of productivity differences is persistent, that capital pro-

Table 6: Transitory and persistent components of factor productivities, markups, and capital intensities in the dynamic technology choice model

	Transitory Component			Persistent Component		
	std($\hat{\alpha}_{it}^L$)	std($\hat{\alpha}_{it}^K$)	$\rho(\hat{\alpha}_{it}^L, \hat{\alpha}_{it}^K)$	std($\bar{\alpha}_{it}^L$)	std($\bar{\alpha}_{it}^K$)	$\rho(\bar{\alpha}_{it}^L, \bar{\alpha}_{it}^K)$
Data	0.07	0.12	0.35	0.23	0.46	-0.21
Model	0.12	0.13	0.97	0.18	0.46	-0.14
	std($\hat{mc}_{it}$)	std($\hat{\kappa}_{it}^K$)	$\rho(\hat{mc}_{it}^L, \hat{\kappa}_{it}^K)$	std($\bar{mc}_{it}^L$)	std($\bar{\kappa}_{it}^K$)	$\rho(\bar{mc}_{it}^L, \bar{\kappa}_{it}^K)$
Data	0.06	0.11	-0.16	0.17	0.55	0.06
Model	0.12	0.03	-0.01	0.16	0.52	-0.16

Notes: Cross-sectional standard-deviations (std) and correlation (ρ) of transitory and persistent components of labor- and capital productivity, α_{it}^L and α_{it}^K as in (9), and capital intensities, κ_{it}, and markups, mc_{it}, as defined in (10) and (11). All second moments are computed as averages over 200 sets of economies simulated with 2,000 plants and for 20 years.

Table 7: Cross-sectional dispersion, adjustment costs and efficiency losses

	All plants	Low markup	High markup
Empirical cross-sectional std($\bar{\kappa}_{it}$)	0.551	0.545	0.622
Simulated cross-sectional std($\bar{\kappa}_{it}$)	0.515	0.499	0.537
Direct adjustment costs relative to			
– total costs (within group)	0.70%	1.20%	0.44%
– plant-level profits (of adjusters)	17.47%	23.54%	11.73%
Indirect efficiency costs			
– exact	3.48%	3.18%	3.80%
– second order approximation (8)			
(actual σ)	3.13%	2.61%	3.73%
... cross-sectional variance	0.59%	0.52%	0.61%
... time-series variation	2.54%	2.09%	3.13%
– second order approximation (8)			
(assuming $\sigma = 1$)	3.91%	4.35%	4.02%
... cross-sectional variance	2.87%	2.53%	3.00%
... time-series variation	1.04%	1.82%	1.02%
Implied loss in profits	7.52%	12.50%	3.96%

Notes: Direct adjustment costs are computed as the sum of incurred adjustment costs ($\phi\pi^*$) relative to (a) the sum of industry-level costs, and (b) the sum of expected profits of adjusting plants in the period of adjustment (π^*). We compute indirect, efficiency costs of the friction as the average unit costs increase compared to minimum unit costs obtained by always setting capital intensity to k_t^*. Exact is based on mean unit cost from simulated model data, while the approximation is based on the second order approximation of unit costs as described in (8). We also provide the misallocation costs when counterfactually assuming the data was generated by a Cobb-Douglas technology with $\sigma = 1$. Profit loss imputation is based on (5). All estimates are based on the baseline model calibration. See notes of Table 6 for further explanation.

ductivity is more disperse than labor productivity and that the persistent component of labor and capital productivity are negatively correlated. The size of the standard deviations and correlations is almost perfectly in line with the data.

Table 7 provides information on the implied capital intensity dispersion for the highest and lowest markup quintile. Again the simulation results are in line with the data; albeit the differences across groups somewhat smaller. In the actual data, the differences between markup groups are roughly 30%, in the numerical model they are about 16%.

In addition, the table reports the implied economic costs of the adjustment friction. Upon adjustment, firms on average forgo roughly 17% of annual profits –i.e. two months of disruption. Since adjustment is infrequent, the direct costs of adjustment are small and well below 1% of total expenditures in the economy.

The indirect, efficiency costs of the friction are, however, larger. On average, unit costs increase by 3.5% compared to their minimum obtained by always setting capital intensity to k_t^*. In terms of foregone profits, the loss is even larger and amounts to 7.5%. In our setup with isoelastic demand, the consumer and producer rents are proportional and hence also the loss due to increased unit costs.

We can use (8) to decompose the efficiency loss into its cross-sectional variance $\mathbb{V}_t^x \log k_{it}$ and its time-series component $(\mathbb{E}_t^x \log k_{it} - k_t^*)^2$. The calibrated high long-run elasticity of substitution decreases the overall costs of misallocation for given deviations of k from its static optimal value, see (8). At the same time it increases the time fluctuations in $\log k_t^*$. Therefore, the cross-sectional variance term becomes of little importance. Instead, if one looks at the simulated data through the lens of a Cobb-Douglas production function, the efficiency loss through the cross sectional dispersion becomes substantially more and the efficiency loss through the time-series term less important. A Cobb-Douglas framework has been widely applied, e.g. in Hsieh and Klenow (2009).

5.3 Robustness checks

Next, we ask how sensitive our results are with respect to the targeted aggregate short-run elasticity, the assumed trend growth of capital intensity, and equating plant to technology age. The literature reports a broad range for the former with most estimates falling in the range $[0.3, 1.3]$, see (Chirinko, 2008). If we lower the target aggregate short-run substitution elasticity, the calibration pushes *up* the long-run elasticity of substitution but lowers the persistence of factor prices to meet the targets for the fluctuations in the labor share. The reverse holds true if we lower the target aggregate short-run elasticity of substitution.

Table 8: Model robustness for calibration to Germany

	$std(\bar{\alpha}^L_{it})$	$std(\bar{\alpha}^K_{it})$	$\rho(\bar{\alpha}^L_{it}, \bar{\alpha}^K_{it})$	$std(\bar{\kappa}_{it})$	unit cost increase (%)
Data	0.23	0.46	-0.21	0.55	-
Baseline	0.18	0.46	-0.14	0.52	3.48
Short-run elasticity 0.5	0.19	0.49	-0.25	0.57	6.51
Short-run elasticity 1.0	0.17	0.40	0.02	0.43	2.13
Zero balanced growth ($\gamma = 0$)	0.18	0.35	-0.04	0.40	3.25
Match D.log(VA) dispersion	0.17	0.47	-0.18	0.53	3.48
Refurbishment	0.18	0.38	-0.04	0.43	3.41

Notes: Columns 1-4 show dispersion and correlation of persistent movements in labor productivity, capital productivity, and capital intensity. Column 5 provides the average percentage increase in unit costs compared to minimum unit costs obtained in the frictionless model. Baseline reports results for the benchmark model calibration, and below rows provide various robustnesses where we change one calibration target or parameter, and (fully) recalibrate the model. In the third and fourth row, target short-run substitution elasticity is changed to 0.5 and 1.0, respectively. In the fifth row, we impose zero trend in the relative factor price, and in the sixth row, we match the cross-firm dispersion in first-differenced log value added, D.log(VA). The seventh row shows robustness when calibrating the model to match 75% as many old plants as observed empirically, which can be thought of as allowing for some plant technology refurbishment. See notes of Table 6 for further explanation.

In terms of productivity and capital intensity dispersions, see Table 8, we slightly overshoot for the lower target elasticity and undershoot the empirical dispersions for the higher target.

The table also reports the implied dispersion for a variant of the model that sets trend growth in capital intensity to zero recalibrating all other parameters. The qualitative results are robust to the trend growth specification, even though dispersions decrease by 20%, in terms of standard deviations. Finally, the table also shows that the results are broadly robust when calibrating to the dispersion of valued added growth, and when allowing technology adjustment through plant refurbishment, that is adjustment without plant closure.

While we recalibrate all other model parameters for the robustness checks above, we also ask how much the contribution of fluctuations in factor prices and trend growth are to the resulting cross sectional dispersions in factor productivities. Table 9 shows the results. Both elements contribute roughly equally to the dispersion of capital intensities and factor productivities, however, trend growth in capital intensity creates less of the negative correlation in labor and capital productivity and also produces less productivity losses – the largest fraction of the productivity losses in the baseline calibration stemming from surprise time series fluctuations in optimal capital intensities, see Table 7.

Table 9: Model counterfactuals for calibration to Germany

	$std(\bar{\alpha}^L_{it})$	$std(\bar{\alpha}^K_{it})$	$\rho(\bar{\alpha}^L_{it}, \bar{\alpha}^K_{it})$	$std(\bar{\kappa}_{it})$	unit cost increase (%)
Data	0.23	0.46	-0.21	0.55	-
Baseline	0.17	0.46	-0.14	0.52	3.48
Zero balanced growth ($\gamma = 0$)	0.17	0.33	0.03	0.37	3.53
No price fluctuations ($\sigma_\omega = 0$)	0.17	0.39	0.11	0.41	0.29

Notes: Rows 3 and 4 provide counterfactuals where we change one model parameter while keeping all other model parameters unchanged. We counterfactually impose zero trend in the optimal capital intensity, and assume a deterministic relative factor price, respectively. See notes of Table 6 and 8 for further explanation.

5.4 Developing economies

Next, we ask whether the model is able to explain international differences. For this, we should expect substantial international differences in the volatility of relative factor prices. In fact, unconditional standard deviations of labor shares point in this direction. The labor share is much more volatile in these countries than in Germany, see the first column of Table 10. For example, this could be the result of political turmoil and interventions in the labor market or more volatile access to international capital markets.

Table 10: Technology choice model calibrated to Chile, Colombia, and Indonesia

(a) Recalibrate σ_ω

		labor share *std* (%)	$std(\bar{\alpha}^L_{it})$	$std(\bar{\alpha}^K_{it})$	$\rho(\bar{\alpha}^L_{it}, \bar{\alpha}^K_{it})$	$std(\bar{\kappa}_{it})$	unit cost incr. (%)	σ_ω
DE	D	3.30	0.23	0.46	-0.21	0.55	–	–
	M	3.30	0.18	0.46	-0.14	0.52	3.48	0.30
CL	D	5.22	0.23	0.58	-0.19	0.66	–	–
	M	5.21	0.21	0.52	-0.38	0.63	5.00	0.38
CO	D	5.07	0.26	0.57	-0.23	0.68	–	–
	M	5.09	0.21	0.52	-0.37	0.63	4.91	0.37
ID	D	5.45	0.26	0.67	-0.27	0.78	–	–
	M	5.44	0.22	0.53	-0.41	0.65	5.14	0.38

(b) Recalibrate σ_ω, σ_z, α, A_0, ξ_i

		labor share *std* (%)	$std(\bar{\alpha}^L_{it})$	$std(\bar{\alpha}^K_{it})$	$\rho(\bar{\alpha}^L_{it}, \bar{\alpha}^K_{it})$	$std(\bar{\kappa}_{it})$	unit cost incr. (%)	σ_ω
DE	D	3.30	0.23	0.46	-0.21	0.55	–	–
	M	3.30	0.18	0.46	-0.14	0.52	3.48	0.30
CL	D	5.22	0.23	0.58	-0.19	0.66	–	–
	M	5.15	0.24	0.43	-0.41	0.57	4.54	0.33
CO	D	5.07	0.26	0.57	-0.23	0.68	–	–
	M	5.04	0.30	0.42	-0.60	0.65	3.90	0.30
ID	D	5.45	0.26	0.67	-0.27	0.78	–	–
	M	5.47	0.21	0.50	-0.47	0.62	3.28	0.30

Notes: The second column specifies D for Data and M for Model. For the three countries CL, CO, ID in Panel (a) we recalibrate the dispersion in the relative factor price, σ_ω, to match the dispersion in the countries' labor share, while in Panel (b) we also recalibrate σ_z, α, A_0, and ξ_i. See notes of Table 6 and 8 for further explanation.

We use these differences in labor share volatility to recalibrate the factor price volatility. Given the shorter available time series for the less developed economies, we assume that their persistence of the labor share is the same as in Germany. In Table 10, we conduct two different calibration strategies for these countries. In Panel (a), we only recalibrate σ_ω and fix all other parameters to the German level. Panel (b), by contrast, shows the results where we also recalibrate the technological parameters and demand shocks (σ_z, α, A_0, ξ_i) to match country-specific moments. In (a), the implied increase in unit costs from misallocation is almost 80% higher in the developing economies, so is the variance of relative factor prices (standard deviation in last column). In (b), when adjusting all other technological parameters, the evidence for less table factor prices and higher efficiency losses vanishes.

6 Capital adjustment frictions

We have seen that frictional technology adjustment is able to produce productivity and capital intensity dispersions in size close to what we observe empirically, that it can explain international differences in the persistent component of productivity differences across plants as well as differences across firms with different markups.

Yet, is it the friction in technology adjustment, or can the observed dispersions be actually explained by any adjustment friction? Asker et al. (2014) show that capital adjustment frictions can lead to sizeable productivity dispersions and are able to explain international differences in capital productivity dispersions as well. However, they do not split up productivity differences across firms in a persistent and a transitory component and do not report cross-factor correlations. We therefore adapt our technology choice model by replacing the technology friction with a capital adjustment friction. As in Asker et al., we allow for both fixed and convex capital adjustment costs. We provide more details on model setup and calibration in Appendix E.

Table 11 reports the results of this exercise. As shown in as in Asker et al. (2014), capital adjustment frictions can explain the overall dispersions in capital productivities well and in our model account for 88% of the total empirical variance. However, the model generates long-lived differences in capital productivity that are too small compared to the data (55% of the variance) and short-lived differences that are too large (330% of the variance). In addition, the correlations between labor and capital productivity show the wrong signs when split into transitory and persistent components. This mechanically implies transitory differences in capital intensity making up a large part (40%) of the model's total capital-intensity variance. Again this stands in sharp contrast to the data. Appendix E shows that these patterns are highly robust to the model calibration.

The reason for this lies in the basic mechanics of *any* model with different degrees of

Table 11: Transitory and persistent components of factor productivities, markups, and capital intensities in the capital adjustment model

	Transitory Component			Persistent Component		
	std($\hat{\alpha}^L_{it}$)	std($\hat{\alpha}^K_{it}$)	$\rho(\hat{\alpha}^L_{it}, \hat{\alpha}^K_{it})$	std($\bar{\alpha}^L_{it}$)	std($\bar{\alpha}^K_{it}$)	$\rho(\bar{\alpha}^L_{it}, \bar{\alpha}^K_{it})$
Data	0.07	0.12	0.35	0.23	0.46	-0.21
Baseline	0.02	0.25	-0.92	0.15	0.37	0.40
	std($\hat{mc}_{it}$)	std($\hat{\kappa}^K_{it}$)	$\rho(\hat{mc}^L_{it}, \hat{\kappa}^K_{it})$	std($\bar{mc}^L_{it}$)	std($\bar{\kappa}^K_{it}$)	$\rho(\bar{mc}^L_{it}, \bar{\kappa}^K_{it})$
Data	0.06	0.11	-0.16	0.17	0.55	0.06
Baseline	0.03	0.27	-0.82	0.15	0.34	-0.38

Notes: Baseline provides model results under the benchmark calibration. See notes of Table 6 and 8 for explanations.

flexibility in labor and capital. When one factor is more flexible than the other, a firm will use the more flexible factor strongly to accommodate shocks to its optimal scale. For example, as demand z in the capital-adjustment model goes up, the firm wants to raise production and will do so by hiring more labor on impact and only subsequently adjust capital. Therefore, capital intensity drops on impact and recovers thereafter. This shows how idiosyncratic shocks to optimal scale translate directly into *transitory* idiosyncratic movements in capital intensity in any model that features different degrees of flexibility of labor and capital. As discussed before, our calibrated model indeed implies too large transitory differences in capital intensity relative to persistent ones.

7 Conclusion

This paper asks whether productivity dispersions should be understood as a result of frictions in technology choice. We have derived qualitative and quantitative implications of such friction and show that these are borne out empirically.

In line with the existing literature, we find large productivity differences across firms/ plants even within narrowly defined industries. We show that most of the differences are long lived and related to highly persistent differences in capital intensity. Finally, grouping the sample by average markup we show that the within group cross-sectional dispersion of capital intensity is largest for the group with the highest markup.

We offer a new explanation to these empirical findings developing a quantitative dynamic model of technology choice, where adjustment of capital intensity is subject to a disruption cost. This model, calibrated to the time series behavior of the labor share, can explain the salient features of the data as well as the cross-country and cross-markup group differences.

The model also allows us to quantify the efficiency and welfare losses arising from the technology friction. We focus on losses in productive efficiency and disregard allocative inefficiency to be conservative in the estimate. Allocative inefficiency in the data shows up as markup differences, which in our model arise from differences in demand elasticities and demand shocks. The quantified welfare losses from productive inefficiency and their differences across countries are modest compared to the literature that includes allocative inefficiencies.

For future work it would hence be interesting to explore in more detail the reasons for large differences across countries in cross-sectional markup dispersions – i.e. in allocative efficiency. Here, the interesting fact is that the cross-sectional markup dispersion is by and large the same in all countries when looking at persistent markup differences, while the dispersion of transitory markup differences starkly differ.

References

Acemoglu, D., Antras, P., and Helpman, E. (2007). Contracts and Technology Adoption. *American Economic Review*, 97(3):916–943.

Amaral, P. S. and Quintin, E. (2010). Limited Enforcement, Financial Intermediation, And Economic Development: A Quantitative Assessment. *International Economic Review*, 51(3):785–811.

Asker, J., Collard-Wexler, A., and De Loecker, J. (2014). Dynamic inputs and resource (mis)allocation. *Journal of Political Economy*, 122(5):1013 – 1063.

Bachmann, R. and Bayer, C. (2013). Wait-and-see business cycles? *Journal of Monetary Economics*, 60(6):704 – 719.

Bachmann, R. and Bayer, C. (2014). Investment dispersion and the business cycle. *American Economic Review*, 104(4):1392–1416.

Bachmann, R., Bayer, C., and Seth, S. (2011). Elflop establishment labor flow panel. *Documentation, IAB*. Documentation, IAB.

Banerjee, A. V. and Moll, B. (2010). Why Does Misallocation Persist? *American Economic Journal: Macroeconomics*, 2(1):189–206.

Bar-Isaac, H., Caruana, G., and Cunat, V. (2012). Search, design, and market structure. *American Economic Review*, 102(2):1140–60.

Bester, H. and Petrakis, E. (1993). The incentives for cost reduction in a differentiated industry. *International Journal of Industrial Organization*, 11(4):519–534.

Blalock, G. and Gertler, P. J. (2009). How firm capabilities affect who benefits from foreign technology. *Journal of Development Economics*, 90(2):192–199.

Buera, F. J., Kaboski, J. P., and Shin, Y. (2011). Finance and Development: A Tale of Two Sectors. *American Economic Review*, 101(5):1964–2002.

Calvo, G. (1983). Staggered prices in a utility-maximizing framework. *Journal of Monetary Economics*, 12(3):383–398.

Cantore, C. and Levine, P. (2012). Getting normalization right: Dealing with 'dimensional constants' in macroeconomics. *Journal of Economic Dynamics and Control*, 36(12):1931–1949.

Chirinko, B. (2008). [sigma]: The long and short of it. *Journal of Macroeconomics*, 30(2):671–686.

David, J., , Hopenhayn, H. A., and Venkateswaran, V. (2013). The Informativeness of Stock Prices, Misallocation and Aggregate Productivity. 2013 Meeting Papers 455, Society for Economic Dynamics.

Foster, L., Haltiwanger, J., and Syverson, C. (2008). Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability? *The American Economic Review*, 98(1):394–425.

Gilchrist, S. and Williams, J. C. (2000). Putty-Clay and Investment: A Business Cycle Analysis. *Journal of Political Economy*, 108(5):928–960.

Gilchrist, S. and Williams, J. C. (2005). Investment, Capacity, and Uncertainty: A Putty-Clay Approach. *Review of Economic Dynamics*, 8(1):1–27.

Gopinath, G., Kalemli-Ozcan, S., Karabarbounis, L., and Villegas-Sanchez, C. (2015). Capital allocation and productivity in south europe. Working Paper 21453, National Bureau of Economic Research.

Gourio, F. (2011). Putty-clay technology and stock market volatility. *Journal of Monetary Economics*, 58(2):117–131.

Gourio, F. and Rudanko, L. (2014). Customer Capital. *Review of Economic Studies*, 81(3):1102–1136.

Henriquez, C. (2008). Stock de Capital en Chile (1985-2005): Metodologia y Resultados. *Central Bank of Chile*, -:–.

Hsieh, C.-T. and Klenow, P. J. (2009). Misallocation and Manufacturing TFP in China and India. *The Quarterly Journal of Economics*, 124(4):1403–1448.

Johansen, L. (1959). Substitution versus Fixed Production Coefficients in the Theory of Economic Growth: A Synthesis. *Econometrica*, 27(2):pp. 157–176.

Kaboski, J. P. (2005). Factor price uncertainty, technology choice and investment delay. *Journal of Economic Dynamics and Control*, 29(3):509–527.

Karabarbounis, L. and Neiman, B. (2013). The global decline of the labor share. *The Quarterly Journal of Economics*.

Leibenstein, H. (1966). Allocative efficiency vs." x-efficiency". *The American Economic Review*, pages 392–415.

Midrigan, V. and Xu, D. Y. (2013). Finance and Misallocation: Evidence from Plant-level Data. *Forthcoming in American Economic Review*, -:–.

Moll, B. (2014). Productivity Losses from Financial Frictions: Can Self-Financing Undo Capital Misallocation? *Forthcoming in American Economic Review*.

Oberfield, E. and Raval, D. (2014). Micro Data and Macro Technology. Working paper, Princeton University.

Peters, M. (2013). Heterogeneous Mark-Ups and Endogenous Misallocation. mimeo, LSE.

Piketty, T. (2011). On the long-run evolution of inheritance: France 18202050. *The Quarterly Journal of Economics*, 126(3):1071–1131.

Piketty, T. (2014). *Capital in the Twenty-First Century.* Harvard University Press.

Raval, D. (2014). The Micro Elasticity of Substitution and Non Neutral Technology. Working paper, Federal Trade Commission.

Restuccia, D. and Rogerson, R. (2008). Policy Distortions and Aggregate Productivity with Heterogeneous Plants. *Review of Economic Dynamics*, 11(4):707–720.

Restuccia, D. and Santaeulalia-Llopis, R. (2015). Land Misallocation and Productivity. Working Papers tecipa-541, University of Toronto, Department of Economics.

Solow, R. M. (1956). A contribution to the theory of economic growth. *The Quarterly Journal of Economics*, 70(1):65–94.

Vial, V. (2006). New Estimates of Total Factor Productivity Growth in Indonesian Manufacturing. *Bulletin of Indonesian Economic Studies*, 42(3):357–369.

Appendices

A Empirics

A.1 Description of the data

German Firm Data: USTAN (Unternehmensbilanzstatistiken)

USTAN is itself a byproduct of the Bundesbank's rediscounting and lending activity. The Bundesbank had to assess the creditworthiness of all parties backing promissory notes or bills of exchange put up for rediscounting (i.e. as collateral for overnight lending). It implemented this regulation by requiring balance sheet data of all parties involved, which were then archived and collected, see Bachmann and Bayer (2013) for details. Our initial sample consists of 1,846,473 firm-year observations. We remove observations from East German firms to avoid a break of the series in 1990. Finally, we drop the following sectors: hospitality (hotels and restaurants), financial and insurance institutions, public health and education sectors. The resulting sample covers roughly 70% of the West-German real gross value added in the private non-financial business sector. In particular, it includes Agriculture, Energy and Mining, Manufacturing, Construction, and Trade.

Chilean Plant Data: ENIA (Encuesta Nacional Industrial Anual)

ENIA is collected by the National Institute of Statistics (*Instituto Nacional de Estadsticas*, INE) and provides plant-level data from 1995 to 2007. ENIA contains information for all manufacturing plants with total employment of at least ten. For the period under analysis, we have a sample of 70,217 plant-year observations. According to INE, this sample covers about 50% of total manufacturing employment.

Colombian Plant Data: EAM (Encuesta Anual Manufacturera)

EAM is a plant-level survey collected by National Institute of Statistics (*Departamento Administrativo Nacional de Estaditicas*, DANE) for the period 1977 to 1991. The survey covers information for all manufacturing plants during 1977-1982, while it only contains data on plants above 10 employees for 1983-1984, and from 1985, small plants are included in small proportion. This results in 103,011 plant-year observations.

Indonesian Plant Data: IBS (Survei Tahunan Perusahaan Industri Pengolahan)

IBS is the Indonesian Manufacturing Survey of Large and Medium Establishments, provided by the National Institute of Statistics (*Badan Pusat Statistik*, BPS). The survey covers all plants with 20 or more employees in the manufacturing sector. Given that the capital stock is reported since 1988 onwards, we exclude earlier years and focus on the period 1988-2010, with 485,052 plant-year observations.

A.2 Sample selection

Starting from the raw data set, we concentrate on describing the general cleaning steps common to all countries, and we provide more information about country-specific cleaning steps at Table 12.

To begin with, we remove observations where firms or plants report extraordinarily large depreciation rates (e.g. due to fire or accident). The reason is that our dynamic model does not capture such cases, and the perpetual inventory method (PIM) will inaccurately measure the actual capital stock after such incidents occur.[14] Next, for those countries where current values of capital stock is not provided (Germany and Colombia), we recompute capital stocks using the PIM. In conducting the PIM, we drop a small amount of outliers, as explained in Section A.4. Further, we do not consider observations where value-added, capital stock, or employment is non-positive or missing.

Moreover, we do not consider observations where firms/plants have missing values in the changes of employment (N), real capital (K) and real value-added (VA).[15] To construct capital productivity, we use the lagged value of capital stock, so we effectively discard the first year of each micro unit. We remove outliers in the levels and in the relative changes of employment, capital, value-added, and factor shares based on 3 standard deviations from the industry-year mean. In addition, we drop firm/plant-year observations whenever the total factor expenditures share is either below 1/3 or above 3/2, and whenever the firm/plant average total factor expenditure share is above 1. These two cleaning steps should exclude units from our analysis which report continuously unreasonably large markups or losses.

Finally, as our empirical results rely on a 5-year moving average filter, we do not consider firm/plant-year observations that have less than 5 consecutive years.

[14] At some cases in the ENIA, EAM, and IBS surveys, plants do not report depreciation conditional on positive capital stock. In order to not loose this observations, we impute the depreciation by capital type and two-digit industry, estimating a random effect model, using as explanatory variable the log-capital stock. To discard rare depreciation events, we drop observations whenever the reported depreciation rate in structures (equipment) is above 40% (60%) yearly. Additionally, we do not consider those cases where the reported depreciation is below 0.1% (1%) in structures (equipment), yearly.

[15] To construct measures of real capital stock we consider an index price by each capital type (when available) using the information of gross fixed capital formation at current and constant prices from National Accounts, while for for value added we use the GDP price deflator.

Table 12: Sample selection

Criterion/Country	Germany	Chile	Colombia	Indonesia
Initial sample	1,846,473	70,217	103,006	485,052
East Germany	-115,201	–	–	–
Additional cleaning steps	–	–	–	-32,618
Imputation capital stock	–	–	–	+37,341
Rare depreciation events	-54,280	-8,197	-6,176	-8,775
Outliers in PIM	-73,784	–	-4,280	–
Missing values	-422,739	-19,589	-29,804	-235,280
Outliers in factor variables	-176,232	-12,375	-24,651	-86,070
Less than 5 consecutive years	-312,452	-15,479	-14,264	-84,885
Final sample	689,665	14,307	23,831	74,765

Notes: Missing values denote the sum of missing values at log value added, log capital, factor shares and log changes in employment, capital and value added. Outliers in factor variables is the sum of all identified outliers at log changes in employment, real capital and real value added, and factor shares. For more information with respect to *Additional cleaning steps* and *Imputation of capital stock* in Indonesia, see Section A.3.

A.3 Specific cleaning and imputation steps for IBS

Before proceeding with the general cleaning steps applied to all datasets, we need to implement some specific corrections in the Indonesia micro data. In doing so, we closely follow Blalock and Gertler (2009). First, we correct for mistakes due to data keypunching. If the sum of the capital categories is a multiple of 10^n (with n being an integer) of the total reported capital, we replace the latter with the sum of the categories. Second, we drop duplicate observations within the year (i.e. observations which have the same values for all variables in the survey but differ in their plant identification number). Third, we re-compute value added whenever their values are not consistent with the formula provided by BPS. Finally, the survey changed their industry classification from *ISIC Rev. 2* in 1998 to *ISIC Rev. 3* in 1999 and to *ISIC Rev. 4* in 2010. We use United Nations concordance tables to construct a consistent time series of four digit industry classification.

Further, the surveys from 1996 and 2006 provides only information on the aggregate capital stock, yet, not disaggregated by capital type (structure and equipment). To construct an economically reasonable estimate of these variables for these years, we use the average reported investment share and capital share of capital type in the preceding and subsequent year, and impute it, multiplying the aggregate capital stock and investment with the respective share.

Finally, we impute capital stock for plants, whenever the survey presents missing values for this variable in plants which reported information in previous and/or subsequent years. Following Vial (2006), we impute capital by type (machinery, vehicles, land and buildings), using the following regression by two-digit sectoral level:

$$\log K_{it} = \beta_0 + \beta_1 \log K_{it-1} + \theta \ln X_{it-1} + \mu_i + \epsilon_{it}$$

where K_{it} is the capital stock of type i, μ_i plant fixed effects and X_{it-1} a set of explanatory variables (total output, input, employees, wages, fuel costs and expenditures on materials, leasing, industrial services and taxes).[16]

A.4 Perpetual inventory method

Whenever the dataset does not directly provide information on a firm's/plant's capital stock at current values (USTAN and EAM), we re-calculate capital stocks using the perpetual inventory method (PIM), in order to obtain economically meaningful capital series. In doing so, we follow (Bachmann and Bayer, 2014). To begin with, we compute nominal investment series using the accumulation identity for capital stocks:

$$p_t^I I_{i,k,t} = K^r_{i,k,t+1} - K^r_{i,k,t} + D^r_{i,k,t},$$

where $K^r_{i,k,t}$ and $D^r_{i,k,t}$ are firm/plant i's reported capital stock and depreciation for capital type k at time t, respectively. Given that capital is reported at historical prices and does not reflect the productive (real) level of capital stock, we apply the PIM to construct economic real capital stock at each type of capital:

$$K_{i,k,1} = \frac{p_1^I}{p_{base}^I} K^a_{i,k,1}; \quad K_{i,k,t+1} = K_{i,k,t}(1 - \delta_{i,k,t}) + \frac{p_t^I}{p_{base}^I} I_{i,k,t}, \ \ \forall t \in [0, T]$$

where $K^a_{i,k,1}$ is the accounting value of the capital stock of type k for the first period we observe the unit, $\frac{p_t}{p_{base}} I_{i,k,t}$ is the real investments in capital k of firm/plant i at time t and $\delta_{i,k,t}$ is the reported depreciation rate of capital k by firm/plant i at time t.[17]

Even though the aforementioned procedure makes sure that values follows a economically meaningful real capital stock series from second period onwards, it is not clear

[16] We evaluate the robustness of the imputation procedure, using linear interpolation as an alternative approach. Our empirical findings are robust to this alternative specification.

[17] The reported depreciation rate is adjusted such that, on average, it coincides with the economic depreciation rate given by National Accounts. To deflate investment series, we compute an investment good price deflator from each country using the information of gross fixed capital formation at current and constant prices from National Accounts.

whether the starting (accounting) input of capital at the unit, $K^a_{i,k,t}$, reflects the productive real value. To account and adjust the first period value of capital we use an iterative approach. In specific, we construct a time average factor ϕ_k for each type of capital. It the first iteration step, the adjustment factor takes value of 1 while capital is equal to its balanced sheet value. That is, $K^n_{i,k,t} = \frac{p^I_t}{p^I_{base}} K^a_{i,k,1}$ for $n = 1$. For the subsequent iterations, capital is computed using PIM:

$$K^n_{i,k,t+1} = K^n_{i,k,t}(1 - \delta_{i,k,t}) + \frac{p_t}{p_{base}} I_{i,k,t},$$

while the ajdustment factor is constructed using the ratio between the capital of consecutive iterations

$$\phi^n_k = \frac{1}{NT} \sum_{i,t} \frac{K^n_{i,k,t}}{K^{n-1}_{i,k,t}}.$$

Finally, the capital stock at the first period we observe the unit is adjusted by the factor ϕ^n_k. We apply the procedure iteratively until ϕ_k converges[18]

$$K^n_{i,k,1} = \phi^{n-1}_k K^{n-1}_{i,k,1}.$$

A.5 Robustness

We conduct four robustness checks. First, we decompose between persistent and transitory components using either a nine year moving average filter or a HP-Filter ($\lambda = 6.25$). Second, we compute the dispersion and correlations of the persistent and transitory component (given a five year moving average filter) using the interquantile range and Spearman's rho. Third, we compute transitory and persistent dispersions, weighting by the firm/plant-year log real value added. Finally, we analyze the linear relation between markups and the persistent component of capital-intensity. To do so, we apply a two-step OLS regression. In particular, we first remove persistent differences in capital intensity that can be explained by markups, size, and age characteristics. Next, we consider the variance of the estimated residual from the first stage, to regress as a function of markups, size and age.

To summarize, our findings are robust to each specification. Transitory productivity

[18]We stop whenenever the value of ϕ_k is below 1.1. At each iteration step we drop 0.1% from the bottom and the top of the capital distribution. This cleaning step makes sure to not consider episodes of extraordinary depreciation at the plant, which implies that using reported depreciation rate (adjusted to have the same average value from National Accounts) do not reflect the capital stock given by the PIM.

differences are positively correlated while persistent differences are negatively correlated. Moreover, differences in factor productivities and capital intensity are predominantly long-lived. Further, the estimated effect of markups on the variance in the persistent component of capital intensity is positive and significant, even after controlling for size and age. Lastly, and related with the latter finding, given that markups, size, and age are standarized in the second step from this OLS regression, we can get an idea of the explanatory importance of each variable. For all countries, markups are at least as important as size when explaining persistent differences in capital-intensity.

Table 13: Robustness: Transitory and persistent components of factor productivities

	std(a^L_{it})	std(a^K_{it})	$\rho(a^L_{it}, a^K_{it})$	std(a^L_{it})	std(a^K_{it})	$\rho(a^L_{it}, a^K_{it})$
	Transitory Component (9Y MA)			Persistent Component (9Y MA)		
DE	0.074	0.140	0.350	0.204	0.406	-0.203
CL	0.190	0.313	0.394	0.188	0.482	-0.206
CO	0.153	0.200	0.471	0.218	0.502	-0.242
ID	0.214	0.415	0.274	0.203	0.583	-0.300
	Transitory Component (HP)			Persistent Component (HP)		
DE	0.062	0.113	0.352	0.236	0.471	-0.223
CL	0.169	0.260	0.447	0.231	0.578	-0.191
CO	0.134	0.159	0.516	0.257	0.569	-0.234
ID	0.196	0.343	0.344	0.256	0.670	-0.270
	Transitory Component (IQR-SP)			Persistent Component (IQR-SP)		
DE	0.071	0.129	0.368	0.276	0.556	-0.189
CL	0.209	0.330	0.479	0.297	0.702	-0.161
CO	0.163	0.207	0.487	0.324	0.721	-0.202
ID	0.231	0.419	0.351	0.334	0.856	-0.257

Notes: Labor productivity, a^L_{it}, and capital productivity, a^K_{it}, as defined in (9). 9YMA: results based on the decomposing between transitory and persistent using a nine year moving average filter. HP: results based on the decomposing between transitory and persistent using a HP-filter ($\lambda = 6.25$) . IQR-SP: Interquartile range and Spearman's rank correlation when applying a five year moving average filter to decompose between frequencies. Factor productivities are demeaned by 4-digit industry and year and expressed in logs. Standard errors are clustered standard errors at the firm/plant level. ρ denotes correlation. DE: Germany, CL: Chile, CO: Colombia, ID: Indonesia.

Table 14: Robustness: Transitory and persistent components of markup and capital intensity

	std($\hat{mc_{it}}$)	std($\hat{\kappa_{it}}$)	$\rho(\hat{mc_{it}}, \hat{\kappa_{it}})$	std($\bar{mc_{it}}$)	std($\bar{\kappa_{it}}$)	$\rho(\bar{mc_{it}}, \bar{\kappa_{it}})$
	Transitory Component (9Y MA)			Persistent Component (9Y MA)		
DE	0.073	0.134	-0.184	0.157	0.490	0.089
CL	0.183	0.295	-0.123	0.152	0.552	-0.097
CO	0.145	0.186	-0.066	0.178	0.594	-0.230
ID	0.207	0.412	-0.130	0.160	0.672	-0.027
	Transitory Component (HP)			Persistent Component (HP)		
DE	0.060	0.108	-0.157	0.175	0.572	0.055
CL	0.163	0.238	-0.089	0.184	0.663	-0.088
CO	0.124	0.146	-0.014	0.206	0.677	-0.231
ID	0.189	0.331	-0.123	0.196	0.779	-0.021
	Transitory Component (IQR-SP)			Persistent Component (IQR-SP)		
DE	0.072	0.117	-0.155	0.223	0.665	0.063
CL	0.209	0.277	-0.106	0.258	0.812	-0.087
CO	0.151	0.184	-0.014	0.289	0.854	-0.257
ID	0.226	0.380	-0.119	0.274	0.992	-0.031

Notes: Markups, mc_{it}, and capital intensity, κ_{it}, as defined in (10) and (11). 9YMA: results based on the decomposing between transitory and persistent using a nine year moving average filter. HP: results based on the decomposing between transitory and persistent using a HP-filter ($\lambda = 6.25$) . IQR-SP: Interquartile range and Spearman's rank correlation when applying a five year moving average filter to decompose between frequencies. Factor productivities are demeaned by 4-digit industry and year and expressed in logs. Standard errors are clustered standard errors at the firm/plant level. ρ denotes correlation. DE: Germany, CL: Chile, CO: Colombia, ID: Indonesia.

Table 15: Robustness: Weighted second moments of factor productivities, markups and capital intensity at different frequencies

	$\text{std}(\hat{\alpha}_{it}^L)$	$\text{std}(\hat{\alpha}_{it}^K)$	$\rho(\hat{\alpha}_{it}^L, \hat{\alpha}_{it}^K)$	$\text{std}(\bar{\alpha}_{it}^L)$	$\text{std}(\bar{\alpha}_{it}^K)$	$\rho(\bar{\alpha}_{it}^L, \bar{\alpha}_{it}^K)$
	Transitory Component (5Y MA)			Persistent Component (5Y MA)		
DE	0.050	0.101	0.316	0.196	0.457	-0.176
CL	0.187	0.281	0.457	0.239	0.551	-0.205
CO	0.143	0.170	0.520	0.260	0.562	-0.239
ID	0.216	0.370	0.349	0.263	0.672	-0.275
	$\text{std}(\hat{mc}_{it})$	$\text{std}(\hat{\kappa}_{it})$	$\rho(\hat{mc}_{it}, \hat{\kappa}_{it})$	$\text{std}(\bar{mc}_{it})$	$\text{std}(\bar{\kappa}_{it})$	$\rho(\bar{mc}_{it}, \bar{\kappa}_{it})$
	Transitory Component (5Y MA)			Persistent Component (5Y MA)		
DE	0.052	0.090	-0.161	0.172	0.503	0.067
CL	0.179	0.259	-0.090	0.183	0.645	-0.087
CO	0.133	0.155	-0.016	0.209	0.670	-0.237
ID	0.207	0.356	-0.123	0.198	0.787	-0.021

Notes: abor productivity, a_{it}^L, and capital productivity, a_{it}^K, as defined in (9). Markups, mc_{it}, and capital intensity, κ_{it}, as defined in (10) and (11). Cross-sectional standard-deviations (std) and correlation (ρ) of transitory and persistent components. Transitory and persistent components are obtained by applying a five year moving average filter (5Y MA). Moments are weighted based on the value-added of the plant/firm. Variables under interest are demeaned by 4-digit industry and year and expressed in logs. Standard errors in parentheses are clustered standard errors at the firm/plant level. DE: Germany, CL: Chile, CO: Colombia, ID: Indonesia.

Table 16: Robustness: Regression on the variance in the unexplained persistent component of capital-intensity

	DE	CL	CO	ID
	$var(\epsilon_{\bar{\kappa}_{it}})$			
Log-Markup	0.024	0.069	0.036	0.057
	(0.003)	(0.017)	(0.019)	(0.011)
Log-Size	-0.026	-0.068	-0.057	0.017
	(0.003)	(0.017)	(0.024)	(0.015)
Log-Age		-	0.044	0.009
		-	(0.018)	(0.011)

Notes: The results are obtained using a two step OLS regression estimation. First, we regress the persistent component of log capital intensity (κ) with respect to the demeaned log of markups, size and age. Second, the variance of the estimated residual from the first stage ($\epsilon_{\bar{\kappa}_{it}}$), is regressed as a function of the standarized log of markups, size and age. Standard errors in parentheses are clustered standard errors at the firm/plant level. DE: Germany, CL: Chile, CO: Colombia, ID: Indonesia.

B Second order approximation of unit costs around k^*

For convenience, let us define the relative factor price by $\tilde{R}_t := \frac{R_t}{W_t}$ and (physical) output per worker by

$$f(k_{it}) := \frac{Y_{it}}{N_{it}} = \left[\alpha k_{it}^{\frac{\sigma-1}{\sigma}} + (1-\alpha)A_t^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}.$$

Subsequently, marginal costs may be expressed as

$$c_{it} = W_t \frac{1+\tilde{R}_t k_{it}}{f(k_{it})}$$

and the first derivative of (log) marginal costs with respect to (log) capital intensity,

$$\begin{aligned}\frac{\partial \log(c_{it})}{\partial \log(k_{it})} &= \frac{\tilde{R}_t k_{it}}{1+\tilde{R}_t k_{it}} - \frac{k_{it} f'(k_{it})}{f(k_{it})} \\ &= \frac{(1-\alpha)\tilde{R}_t k_{it} - \alpha k_{it}^{\frac{\sigma-1}{\sigma}}}{(1+\tilde{R}_t k_{it})(\alpha k_{it}^{\frac{\sigma-1}{\sigma}} + (1-\alpha)A_t^{\frac{\sigma-1}{\sigma}})}\end{aligned}$$

Let us denote above denominator by $D \equiv (1+\tilde{R}_t k_{it})(\alpha k_{it}^{\frac{\sigma-1}{\sigma}} + (1-\alpha)A_t^{\frac{\sigma-1}{\sigma}})$, and obtain the second derivative as

$$\frac{\partial^2 \log(c_{it})}{\partial \log(k_{it})^2} = \frac{\left[(1-\alpha)A_t^{\frac{\sigma-1}{\sigma}}\tilde{R}_t - \frac{\sigma-1}{\sigma}\alpha k_{it}^{-\frac{1}{\sigma}}\right]k_{it}D - \left[(1-\alpha)A_t^{\frac{\sigma-1}{\sigma}}\tilde{R}_t k_{it} - \alpha k_{it}^{\frac{\sigma-1}{\sigma}}\right]D' k_{it}}{D^2}.$$

The cost-minimizing capital intensity k^* implies $\frac{\partial \log(c_{it})}{\partial \log(k_{it})}\Big|_{k_{it}=k^*} = 0$, and the second derivative evaluated at $k_{it} = k^*$, where $(1-\alpha)A_t^{\frac{\sigma-1}{\sigma}}\tilde{R}_t k_{it}^* = \alpha k_{it}^{*\frac{\sigma-1}{\sigma}}$, is

$$\begin{aligned}\frac{\partial^2 \log(c_{it})}{\partial \log(k_{it})^2}\Big|_{k_{it}=k^*} &= \frac{(1-\alpha)A_t^{\frac{\sigma-1}{\sigma}}\tilde{R}_t k_{it}^* - \frac{\sigma-1}{\sigma}\alpha k_{it}^{*\frac{\sigma-1}{\sigma}}}{D} \\ &= \frac{(1-\alpha)A_t^{\frac{\sigma-1}{\sigma}}\frac{1}{\sigma}\tilde{R}_t k_{it}^*}{(1+\tilde{R}_t k^*)((1-\alpha)A_t^{\frac{\sigma-1}{\sigma}}\tilde{R}_t k^* + (1-\alpha)A_t^{\frac{\sigma-1}{\sigma}})} = \frac{1}{\sigma}\frac{\tilde{R}_t k^*}{(1+\tilde{R}_t k^*)^2},\end{aligned}$$

where the second equation results again from $(1-\alpha)A_t^{\frac{\sigma-1}{\sigma}}\tilde{R}_t k^* = \alpha k^{*\frac{\sigma-1}{\sigma}}$. The 2nd order Taylor expansion directly follows as

$$\log(c_{it}) - \log(c^*) \approx \sigma^{-1}\frac{\tilde{R}_t k^*}{(1+\tilde{R}_t k^*)^2}\frac{1}{2}(\log(k_{it}) - \log(k^*))^2.$$

C Dynamic Planning Problem

C.1 Existence and uniqueness

In the following, we show the existence and uniqueness of the model described by (1), (12), (13), and (14).

Assumption 1: $\alpha \leq \frac{1}{1+\xi}$.

Lemma: The function $\pi^*(k,z,\omega)$ is bounded from above and below in k, $\forall z,\omega$.

Proof: Since $\pi^*(k,z,\omega)$ is continuous, it is sufficient to show that $\lim_{k\to\infty}|\pi^*(k,z,\omega)| < \infty$. If this is the case, then $\pi^*(k,z,\omega)$ is bounded for $k\to\infty$ and by the Weierstrass extreme value theorem, it is bounded for any finite interval $[0,c]$ $\forall c\in\Re$ and hence bounded everywhere. Defining $f(k) := \frac{y}{N} = \left[\alpha k^{\frac{\sigma-1}{\sigma}} + (1-\alpha)A^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}$, see (6), and using (1), we obtain profits as

$$\pi^*(k,z,\omega) = \frac{\xi}{1-\xi}\mathbb{E}[z^{\xi}]^{\frac{1}{\xi}}\left[\frac{\mathbb{E}[W+Rk]}{f(k)}\right]^{\frac{\xi-1}{\xi}}.$$

Let us check whether $\lim_{k\to\infty}|\pi^*(k,z,\omega)|$ exists. It suffices to check $\frac{f(k)}{\mathbb{E}[W+Rk]}$; for $\sigma\neq 1$:

$$\begin{aligned}\lim_{k\to\infty}\frac{f(k)}{\mathbb{E}[W+Rk]} &\overset{l'Hospital}{=} \lim_{k\to\infty}\frac{f(k)^{\frac{1}{\sigma}}\alpha k^{-\frac{1}{\sigma}}}{\mathbb{E}[R]} = \frac{\alpha}{\mathbb{E}[R]}\lim_{k\to\infty}\left[\frac{f(k)}{k}\right]^{\frac{1}{\sigma}} \\ &= \frac{\alpha}{\mathbb{E}[R]}\lim_{k\to\infty}\left[\alpha + (1-\alpha)A^{\frac{\sigma-1}{\sigma}}k^{-\frac{\sigma-1}{\sigma}}\right]^{\frac{1}{\sigma-1}} < \infty \qquad (17)\end{aligned}$$

and for $\sigma = 1$:

$$\lim_{k\to\infty}\frac{f(k)}{W+\mathbb{E}[R]k} = \lim_{k\to\infty}\frac{k^{\alpha}A^{1-\alpha}}{W+\mathbb{E}[R]k} = \frac{\alpha A^{1-\alpha}}{\mathbb{E}[R]}\lim_{k\to\infty}k^{\alpha-1} < \infty \qquad (18)$$

Hence, $\pi^*(k,z,\omega)$ is bounded.

Lemma: Let us define the operator T by posing $(Tv)(k,z,\omega)$ equal to the right-hand-side of equation (14). This operator is defined on the set $\mathcal{B}$ of all real-valued, bounded and continuous functions with domain $\Re_+ \times \Re_{++} \times \Re_{++}$. Then T (i) preserves boundedness,

(ii) preserves continuity, and (iii) satisfies Blackwell's sufficient conditions.
Proof: $\pi^*(k, z, \omega)$ is continuous, concave, and bounded in the set of state variables.
(i) Consider $u \in \mathcal{B}$ bounded below by $\underline{u}$ and bounded above by $\overline{u}$. Then $(Tu)(k, z, \omega)$ is bounded from below and above since $\pi^*(k, z, \omega)$ is bounded as shown before.
(ii) Next, we show that (Tu) is continuous. We note that (Tu) is the maximum of a constant and a function. Since the function is the sum of two continuous functions $\pi^*(k, z, \omega)$ and $u(k, z, \omega)$, (Tu) is continuous.
(iii) Finally, we need to show that (Tu) satisfies monotonicity and discounting. We note that if $u_1, u_2 \in \mathcal{B}$ and $u_1(k, z, \omega) < u_2(k, z, \omega)$ for all k, z and ω, then integrating with respect to the distributions of z and ω preserves the inequality and hence monotonicity holds.
We can show discounting since for any $u \in \mathcal{B}$ and any constant $a \in \Re$, it holds that

$$(T[u + a])(k, z, R) = (Tu)(k, z, R) + \beta a.$$

Blackwell's sufficient conditions for a contraction holds.
Propositon: The model described by (1), (12), (13), and (14) has exactly one solution (in the metric space $\mathcal{B}$).
Proof: We know from Lemma 2 that T defines a contraction mapping on the metric space $\mathcal{B}$ with modulus β. Existence and uniqueness then follow from the Contraction Mapping Theorem.

C.2 Computation

To solve the model numerically, we discretize the state space. We apply Tauchen's algorithm with 15 grid point to discretize the relative factor price process ω and demand shocks z. We use 200 grid points for capital intensity, which spans a sufficiently wide log-spaced grid with grid points not more than 4% distanced from each other, with 4% being the calibrated annual drift according to the calibration of γ. Adjustment cost draw ϕ is discretized into 200 bins. We solve the model using value function iteration.

D Further Details: Technology Choice Model

D.1 Dispersions by Markup Quintile

Table 17: Dispersion of persistent movements in capital intensity: Germany

	std($\bar{\kappa}_{it}^{K}$)	Q1	Q2	Q3	Q4	Q5
Markup	Data	0.545	0.512	0.519	0.539	0.622
	Model	0.499	0.487	0.493	0.503	0.537
Size	Data	0.610	0.525	0.495	0.501	0.509
	Model	0.504	0.507	0.508	0.501	0.505

Note: Q1-Q5 denote the five quintile groups for markup and size, respectively. We reported dispersions in persistent capital intensity movements per per quintilie group.

D.2 Further details on calibration

In the baseline model, we obtain and calibrate depreciation rate using the average depreciation value it the firm-level data in Germany. To do so, we first construct capital series at each firm using PIM and adjust reported depreciation rate at each capital type such that it coincides with the economic depreciation rate given by the *Volkswirtschaftliche Gesamtrechnung* (VGR).

For γ, we can obtain an estimate using different combinations of the geometric yearly growth rate of real GDP, manufacturing real output and capital stock relative to population, labor force and manufacturing employment. Our estimates go from 2% using real GDP-Population to 4.3% in Capital stock-Labor Force and 5.8% taking manufacturing real output-manufacturing Employees. As the bulk of the obtained estimates lies close to 4%, we use this value as benchmark.[19]

Further, we calibrate the average demand elasticity ξ_i for 5 equally large groups using USTAN data. Next, we construct the average markup at the firm, compute the average markup in the economy and remove the industry-year fixed effects based on the four-digit industry classification. Finally, we split the sample in 5 equally large groups and we compute the average group markup.

[19]To obtain these estimates we used Penn World Tables (PWT, 8.0), except for the manufacturing-specific series. For the latter, we took National Statistics and ILO Statistics.

D.3 Identification

We check whether our model calibration strategy well identifies the model parameters by computing the elasticity of target moments with respect to model parameters. In particular, we use central finite differences of plus/minus two percent to compute the gradient. Table 18 shows the matrix containing in rows the elasticity of a given moment with respect to all parameters. Moments and parameters are sorted corresponding the discussion in Section 5 relating model parameters to calibration targets. The diagonal elements of the Jacobian matrix reconfirm our the preceding discussion. E.g. a higher long-run elasticity of substitution increases the short-run elasticity of substitution. Furthermore, Table 18 shows that our model is (locally) well identified since the Jacobian matrix has full rank.

Table 18: Elasticity of target moments and parameters

	σ	λ_ϕ	σ_z	ρ_ω	σ_ω	α	A_0	μ_z
Short-run substitution elasticity	1.63	0.53	-0.02	7.05	1.23	1.99	-1.02	0.00
Share of old plants	-0.17	-0.29	-0.09	-0.80	-0.39	-0.87	0.59	0.00
Dispersion of log(VA)	0.00	-0.00	0.98	-0.00	0.01	0.01	-0.09	0.00
Labor share autocorrelation	0.43	0.09	-0.04	1.30	0.27	0.38	-0.20	0.00
Labor share dispersion	1.72	0.35	0.00	4.72	1.79	3.85	-2.29	-0.00
Transformed capital share	-0.00	0.00	-0.00	0.03	-0.01	0.91	-0.62	0.00
Transformed labor share	2.04	-0.01	0.00	-0.06	-0.03	-0.31	0.20	-0.00
Average expenditures	0.05	0.01	-0.10	0.14	0.08	0.37	1.75	1.00

Notes: This table is based on the baseline calibration for Germany and provides the elasticities of the calibration targets with respect to the model parameters.

E Further Details: Capital Adjustment Model

E.1 Model setup and calibration

We assume a one-period production lag as an adjustment friction on labor and instead of the frictional technology choice, we assume a disruption cost of capital adjustment and convex capital adjustment costs. Analogously to (1), we first define the profit maximizing output/employment decision and the corresponding maximal level of expected next period's profits

$$\pi^{CA*}(K, z, \omega) = \max_{N'} \mathbb{E}_{z',\omega'} \left\{ \frac{z'^{\xi} \left[y(K, N')\right]^{1-\xi}}{1-\xi} - WN' - RK \right\},$$

where output y is given by

$$y(K, N) = \left[\alpha K^{\frac{\sigma-1}{\sigma}} + (1-\alpha)(AN)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}.$$

Given the disruption cost, the firm chooses between adjusting the stock of capital and staying put every period, the value of which being v^a and v^n, respectively. On the other side, the convex cost renders large capital adjustments less attractive. The firm's dynamic problem is described by the following Bellmann equation.

$$\begin{aligned}
v(K, z, \omega) &= \beta \max \left\{v^a(K, z, \omega), v^n(K, z, \omega)\right\} \\
v^a(K, z, \omega) &= \max_{K'} \left\{(1-\phi^F)\pi^{CA*}(K', z, \omega) - \phi^C K \left(\frac{K'-K}{K}\right)^2 + \mathbb{E}_{z',\omega'} \left[v(K', z', \omega')\right]\right\} \\
v^n(K, z, \omega) &= \pi^{CA*}((1-\delta)K, z, \omega) + \mathbb{E}_{z',\omega'} \left[v((1-\delta)K, z', \omega')\right]
\end{aligned}$$

Our calibration strategy corresponds as closely as possible with the one employed in the technology adjustment model. We identify the volatility of demand shocks σ_z from value added growth fluctuations, we choose the production function parameters to match $\psi_{N,K}$ and to match an aggregate short-run elasticity of 0.75, and we also match the labor share fluctuations. Again, we simulate five groups of firms with different demand elasticities to capture persistent markup differences across the five empirical quintiles. There is one major difference in the calibration strategy: To calibrate fixed and convex adjustment costs, we target the skewness and kurtosis of gross investment rates for the German USTAN data as in Bachmann and Bayer (2013).

E.2 Robustness

Table 19 shows that the results are robust to alternative calibrations of the capital adjustment model. That is, to fixing the parameters of the ω-process to the values calibrated for technology adjustment and to matching the variance of value added growth instead of value added. Matching value added dispersions, creates substantially larger shocks to z than matching value added growth dispersions and is closer to Asker et al.'s calibration and results.

The qualitative results are not altered by any of the considered calibration strategies: the cross-factor correlations show the wrong sign compared to the data and the transitory differences in capital intensity explain counterfactually about 40% of the total capital-intensity variance.

Table 19: Robustness of capital adjustment costs model, Germany

	Transitory Component			Persistent Component		
	std($\hat{\alpha}^L_{it}$)	std($\hat{\alpha}^K_{it}$)	$\rho(\hat{\alpha}^L_{it}, \hat{\alpha}^K_{it})$	std($\bar{\alpha}^L_{it}$)	std($\bar{\alpha}^K_{it}$)	$\rho(\bar{\alpha}^L_{it}, \bar{\alpha}^K_{it})$
Data	0.07	0.12	0.35	0.23	0.46	-0.21
Baseline	0.02	0.25	-0.92	0.15	0.37	0.40
D.log(VA)	0.01	0.14	-0.91	0.15	0.23	0.74
Ela. 0.5	0.01	0.22	-0.86	0.14	0.41	0.62
Ela. 1.0	0.03	0.29	-0.92	0.15	0.41	0.30
50% σ_ω	0.02	0.31	-0.94	0.15	0.38	0.34
	std($\hat{mc}_{it}$)	std($\hat{\kappa}^K_{it}$)	$\rho(\hat{mc}^L_{it}, \hat{\kappa}^K_{it})$	std($\bar{mc}^L_{it}$)	std($\bar{\kappa}^K_{it}$)	$\rho(\bar{mc}^L_{it}, \bar{\kappa}^K_{it})$
Data	0.06	0.11	-0.16	0.17	0.55	0.06
Baseline	0.03	0.27	-0.82	0.15	0.34	-0.38
D.log(VA)	0.02	0.15	-0.93	0.15	0.16	-0.31
Ela. 0.5	0.02	0.23	-0.85	0.16	0.34	-0.59
Ela. 1.0	0.03	0.32	-0.79	0.15	0.39	-0.36
50% σ_ω	0.04	0.33	-0.88	0.15	0.35	-0.38

Notes: In the third row, D.log(VA) is as the baseline model but targets the cross sectional dispersion of first differences of log value added instead of the dispersion in log value added. Ela. 0.5 and 1.0 refer to changing the target aggregate short-run substitution elasticity to 0.5 and 1.0, respectively. 50% σ_ω recalibrates the model with a 50% smaller dispersion in relative factor dispersion. See notes of Table 6 and 8 for further explanation.