ONLINE APPENDIX to “Capital-Reallocation Frictions and Trade Shocks” by Andrea Lanteri, Pamela Medina, and Eugene Tan

A Data and Measurement

In this appendix, we provide additional descriptive statistics and discuss further details on our measurement strategy.

A.1 Industry Shares, Number of Firms and Exit Rates

For our analysis, we consider the six largest 2-digit manufacturing industries in Peru. In 2007, the latest economic census year, the six industries we analyze represented approximately 70 and 54 percent of Peruvian manufacturing employment and sales, respectively. In Table A1 the first and second columns show the industry shares of employment and sales for each of the six industries, respectively.

Moreover, columns 3-5 of Table A1 document the relevance of our correction in the measurement of exit, which relies on matching the EEA with the firm registry, in the aggregate and by industry. The third column shows the number of firms throughout the sample period in our EEA sample. The fourth column describes the raw exit rate of the sample. In particular, this exit rate is constructed considering that the maximum year that a firm appears on the sample correspond to the the exit year. As mentioned in Section 4.1, this approach overestimates exit due to the fact that the EEA is a sample for small firms, and thus attrition from the survey can be misinterpreted as exit. The fifth column corresponds to the EEA exit rates corrected with the Peruvian firms' registry for 2007-2013. For all firms that we can match based on tax ID, we replace the EEA exit date with the exit date from the registry. As shown, exit rates in all industries decrease considerably, as well as the aggregate one.

Industry	Employment Share	Sales Share	N. Firms	Exit Raw	Exit Corrected
Food-Beverages	11.49	12.71	1,058	38.96	30.80
Textiles	13.38	6.81	728	20.74	12.89
Apparel	23.09	7.24	926	32.94	23.92
Printing	5.84	5.91	881	30.70	20.93
Chemical	9.86	13.31	603	14.34	7.94
Mach-Eq nec	5.71	7.57	565	28.73	13.07
All	69.36	53.54	4,761	27.36	18.39

Table A1: Summary Statistics of Samples and Exit Rates.

Notes: The table reports summary statistics for the six industries of analysis. The first and second columns show the employment and sales shares of each of these industries in the Peruvian manufacturing sector. The third column reports the number of firms in our sample. The fourth and fifth columns exhibit the exit rates in the data without and with the correction using the Peruvian firms' registry.

A.2 Alternative Definitions of Revenue Productivity

In this section, we clarify the distinction between two definitions of revenue productivity, namely the one we adopt, as in Asker, Collard-Wexler, and De Loecker (2014), and the one used, for instance, by Hsieh and Klenow (2009).

Recall the key assumptions on technology and demand, which we use as a guide for measurement (Section 4.2) and posit in our theoretical model (Section 3). The production function is

$$y_{jt} = s_{jt} k_{jt}^{\alpha} n_{jt}^{1-\alpha} \tag{A1}$$

where s_{jt} is physical total factor productivity, or TFPQ.

Demand for firm j's output is

$$y_{jt} = B p_{jt}^{-\epsilon} \tag{A2}$$

where, for simplicity of exposition, we focus on a stationary equilibrium and thus set the aggregate component $B_t = B$ equal to a constant.

Thus, revenue can be expressed as follows:

$$p_{jt} y_{jt} = B^{\frac{1}{\epsilon}} s_{jt}^{\theta} k_{jt}^{\theta\alpha} n_{jt}^{\theta(1-\alpha)} \tag{A3}$$

with $\theta \equiv \frac{\epsilon-1}{\epsilon}$.

We define (log) revenue productivity as in Asker, Collard-Wexler, and De Loecker

(2014):

$$\log(\omega_{jt}) \equiv \log(p_{jt}y_{jt}) - \theta\alpha\log(k_{jt}) - \theta(1-\alpha)\log(n_{jt}) = \frac{1}{\epsilon}\log(B) + \theta\log(s_{jt}) \tag{A4}$$

Hsieh and Klenow (2009) define (log) revenue productivity as follows:

$$\log(\tilde{\omega}_{jt}) \equiv \log(p_{jt}s_{jt}) = \log(p_{jt}y_{jt}) - \alpha\log(k_{jt}) - (1-\alpha)\log(n_{jt}) \tag{A5}$$

$$= \frac{1}{\epsilon}\log(B_t) + \theta\log(s_{jt}) - \frac{1}{\epsilon}\left[\log(y_{jt}) - \log(s_{jt})\right] \tag{A6}$$

$$= \log(\omega_{jt}) - \frac{1}{\epsilon}\left[\log(y_{jt}) - \log(s_{jt})\right] \tag{A7}$$

Marginal revenue products of capital and labor (in logs) are defined as follows:

$$\log(MRPK_{jt}) = \log(\alpha\theta) + \log(p_{jt}y_{jt}) - \log(k_{jt}) \tag{A8}$$

$$\log(MRPN_{jt}) = \log((1-\alpha)\theta) + \log(p_{jt}y_{jt}) - \log(n_{jt}) \tag{A9}$$

Then, Hsieh and Klenow (2009) obtain the following expression:

$$\log(\tilde{\omega}_{jt}) = const + \alpha\log(MRPK_{jt}) + (1-\alpha)\log(MRPN_{jt}) \tag{A10}$$

For simplicity, assume $MRPN_{jt}$ is equalized across j, as implied by the model of Section 3. Then, $\log(\tilde{\omega}_{jt})$ has the same statistical properties of $\log(MRPK_{jt})$, which in turn depends on any distortions or adjustment frictions in capital, whereas $\log(\omega_{jt})$ has the same statistical properties of $\log(s_{jt})$, i.e., is exogenous with respect to distortions and adjustment frictions.

A.3 Depreciation Rates

To construct firm-level depreciation rates we proceed as follows. First, for each firm j and year t, we construct the share S_{jlt} of capital stock held in capital of type l. Next, we use data from the U.S. Bureau of Economic Analysis (BEA) to obtain capital-type-year-specific depreciation rates δ_{lt} for the U.S. We then use these depreciation rates to compute firm-year-specific average depreciation rates, using the following formula:

$$\delta_{jt} = \sum_{l} S_{ilt}\delta_{lt} \tag{A11}$$

Specifically, we obtain the depreciation rates from Tables 2.1 and 2.4 of the Fixed Asset tables of the National Income and Products Accounts. Figure A1 provides further details on the distribution of average depreciation rates.

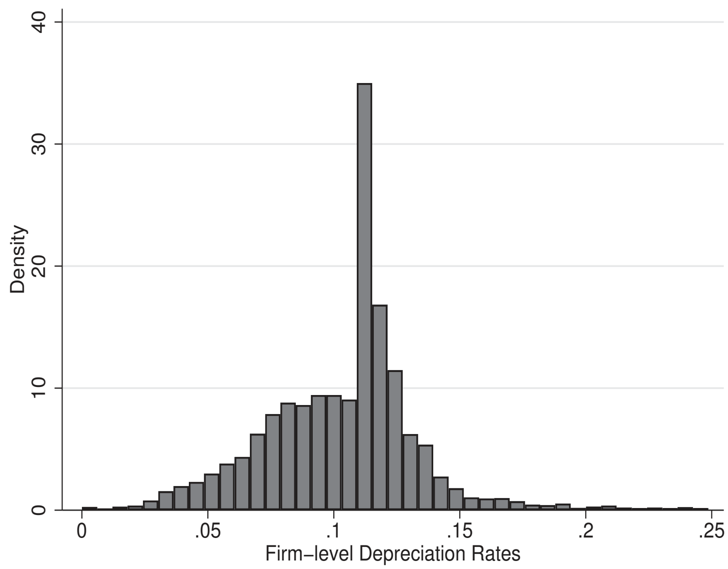


Figure A1: Distribution of Imputed Firm-level Depreciation Rates.

Notes: This figure is a histogram of firm-level depreciation rates, defined in equation (A11). Figure shows $\delta_{jt} < 0.25$ for expositional purposes.

B Capital-Reallocation Frictions

In this appendix, we provide additional empirical evidence on the importance of capital-reallocation frictions for Peruvian manufacturing firms.

B.1 Dispersion of MRPK and Volatility of ω

Figure B1 shows a scatter plot of the dispersion in MRPK against the volatility of revenue productivity ω in our sample. Each observation corresponds to an industry-year pair. Thus, dispersion in MRPK refers to the within industry-year standard deviation of MRPK, while volatility of ω refers to the standard deviation of the innovations to ω, computed as the residual of an AR(1) process. We also overlay the implied predicted dispersion in MRPK by fitting an OLS regression line.

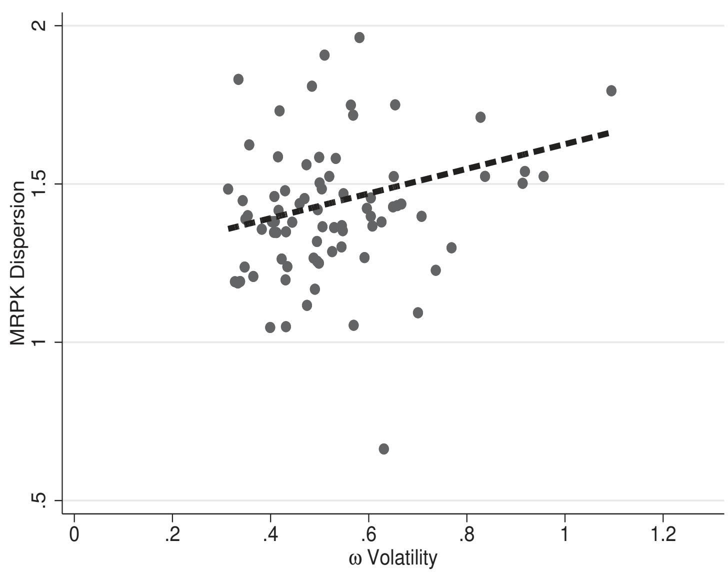


Figure B1: Dispersion of MRPK and Volatility of ω.

Notes: Each observation is a single industry-year pair with associated MRPK dispersions and ω volatility. The solid line is generated by a (weighted) OLS regression with a slope of 0.39 (0.01).

B.2 Distribution of Investment Rates

We report here the summary statistics related to the distribution of investment rates. The investment rate of firm j in year t is constructed as $\frac{i_{jt}}{k_{jt}}$, with

$$i_{jt} \equiv k_{j,t+1} - (1 - \delta_{jt})\, k_{jt}$$

where δ_{jt} is the depreciation rate. Section 4 in the main text and Appendix A.3 provide more details on how the firm level depreciation rates are constructed, and report the distribution and characteristics of our constructed depreciation rates. We winsorize the distribution of investment rates at the 2.5th and 97.5th percentile. Notice that the key features of the distribution of investment rates that we target in the quantitative model are not significantly different if we use a constant firm depreciation rate for all firms.

As is common in firm-level data, investment is lumpy and volatile, which is reflected in Figure B2 and Table B1.

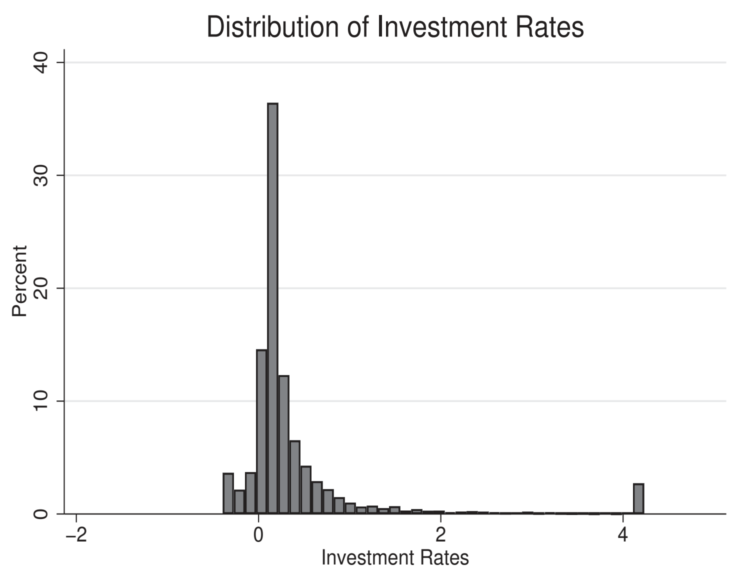


Figure B2: Distribution of Investment Rates.

Notes: The figure is a histogram of firm-level investment rates. Firm-level investment rates are winsorized at the 2.5th and 97.5th percentile.

Industry	Food	Textiles	Apparel	Printing	Chemical	Mach.
Median	0.159	0.159	0.188	0.169	0.158	0.170
St. Dev.	0.868	0.778	0.917	0.870	0.685	0.941
Fraction $\frac{i}{k} < 0$	0.101	0.085	0.121	0.120	0.110	0.123
Inaction (fraction $\frac{\lvert i \rvert}{k} < 10\%$)	0.186	0.188	0.175	0.142	0.227	0.196

Table B1: Summary Statistics of the Distribution of Investment Rates.

Notes: The table reports the main summary statistics of the firm-level investment rates by 2-digit industry. Firm-level investment rates are winsorized at the 2.5th and 97.5th percentile. The first and second rows report the median and standard deviation, respectively. The third row shows the fraction of observations with negative investment rates. Finally, the fourth row refers to the percentage of observations on the inaction region (absolute value of investment rates below 10%).

B.3 Dynamics of MRPK: Transition Matrices

In this section, we report the transition matrices for terciles of productivity ω. We then report the transition matrices for MRPK terciles, allowing for exit as an additional state, and by industry.

B.3.1 Transition Matrices for ω

One natural question is whether the asymmetric persistence of MRPK is driven by asymmetric ω shocks. It is worth highlighting that the persistence of ω has no impact on the persistence of MRPK if firms can easily adjust their capital stock.[42] However, given that we argue that reallocation frictions are likely to be sizable, we also estimate the transition probabilities for ω. Table B2 shows that generally ω does *not* exhibit substantial asymmetry in persistence; if anything, it appears to be more persistent in the right tail. Table B3 corroborates that notion by estimating the ω transition matrices by industry.

		at $t+1$		
		1	2	3
Tercile at t	1	0.71	0.23	0.06
		(0.01)	(0.01)	(0.00)
	2	0.23	0.60	0.17
		(0.00)	(0.01)	(0.00)
	3	0.04	0.20	0.76
		(0.00)	(0.00)	(0.00)

Table B2: Transition Probabilities of ω.

Notes: The table reports the estimated transition probabilities for terciles of the ω distribution. Bootstrapped standard errors in parentheses.

[42] Tan (2021) proves this result.

		at $t+1$		
		1	2	3
Tercile at t	1	0.71	0.24	0.06
		(0.02)	(0.02)	(0.01)
	2	0.22	0.60	0.18
		(0.01)	(0.02)	(0.01)
	3	0.04	0.20	0.76
		(0.01)	(0.01)	(0.01)

(a) Food

		at $t+1$		
		1	2	3
Tercile at t	1	0.71	0.19	0.09
		(0.01)	(0.01)	(0.01)
	2	0.25	0.61	0.14
		(0.01)	(0.01)	(0.01)
	3	0.04	0.21	0.75
		(0.00)	(0.01)	(0.01)

(b) Textiles

		at $t+1$		
		1	2	3
Tercile at t	1	0.72	0.25	0.04
		(0.02)	(0.02)	(0.01)
	2	0.23	0.59	0.18
		(0.01)	(0.02)	(0.01)
	3	0.05	0.24	0.71
		(0.01)	(0.01)	(0.01)

(c) Apparel

		at $t+1$		
		1	2	3
Tercile at t	1	0.68	0.24	0.08
		(0.02)	(0.02)	(0.01)
	2	0.25	0.59	0.16
		(0.01)	(0.02)	(0.01)
	3	0.06	0.24	0.71
		(0.01)	(0.01)	(0.01)

(d) Printing

		at $t+1$		
		1	2	3
Tercile at t	1	0.75	0.22	0.03
		(0.01)	(0.01)	(0.00)
	2	0.19	0.63	0.18
		(0.01)	(0.01)	(0.01)
	3	0.02	0.17	0.81
		(0.00)	(0.01)	(0.01)

(e) Chemicals

		at $t+1$		
		1	2	3
Tercile at t	1	0.61	0.28	0.11
		(0.02)	(0.02)	(0.02)
	2	0.26	0.58	0.16
		(0.02)	(0.02)	(0.01)
	3	0.04	0.16	0.80
		(0.01)	(0.01)	(0.01)

(f) Machinery Eq

Table B3: Transition Matrices for ω by Industry.

Notes: The table reports the estimated transition probabilities for terciles of the ω distribution for each of the 2-digit industries in our analysis. Bootstrapped standard errors in parentheses.

B.3.2 MRPK Transition Matrices: Including Exit

Table B4 shows the transition matrix for terciles of the MRPK distribution considering the fourth state of exit. To this end, we use the corrected exit measure described in Section 4.2. The left-tail asymmetry in the persistence of MRPK is robust to the inclusion of the exit state.

		at $t+1$			
		1	2	3	exit
Tercile at t	1	0.62	0.12	0.01	0.25
		(0.01)	(0.00)	(0.00)	(0.01)
	2	0.15	0.55	0.10	0.20
		(0.00)	(0.01)	(0.00)	(0.01)
	3	0.02	0.13	0.52	0.33
		(0.00)	(0.00)	(0.01)	(0.01)

Table B4: Transition Probabilities of MRPK, with Exit.

Notes: The table reports the estimated transition probabilities for terciles of the MRPK distribution. Bootstrapped standard errors in parentheses.

B.3.3 MRPK Transition Matrices: by Industry

Table B5 shows the transition matrix for terciles of the MRPK distribution for each of the 2-digit industries in our analysis. In all our industries, we observe the left-tail asymmetry in the persistence of MRPK, i.e, our results hold broadly at the industry level and are not driven by any particular 2-digit industry.

		at $t+1$		
		1	2	3
Tercile at t	1	0.80	0.18	0.02
		(0.01)	(0.01)	(0.00)
	2	0.20	0.67	0.13
		(0.01)	(0.02)	(0.01)
	3	0.06	0.23	0.72
		(0.01)	(0.01)	(0.02)

(a) Food

		at $t+1$		
		1	2	3
Tercile at t	1	0.83	0.16	0.01
		(0.01)	(0.01)	(0.00)
	2	0.20	0.71	0.10
		(0.01)	(0.01)	(0.01)
	3	0.05	0.21	0.74
		(0.01)	(0.01)	(0.01)

(b) Textiles

		at $t+1$		
		1	2	3
Tercile at t	1	0.78	0.18	0.04
		(0.01)	(0.01)	(0.01)
	2	0.20	0.67	0.13
		(0.01)	(0.01)	(0.01)
	3	0.06	0.20	0.75
		(0.01)	(0.01)	(0.01)

(c) Apparel

		at $t+1$		
		1	2	3
Tercile at t	1	0.83	0.16	0.01
		(0.01)	(0.01)	(0.00)
	2	0.17	0.70	0.13
		(0.01)	(0.01)	(0.01)
	3	0.02	0.24	0.74
		(0.01)	(0.01)	(0.02)

(d) Printing

		at $t+1$		
		1	2	3
Tercile at t	1	0.85	0.14	0.01
		(0.01)	(0.01)	(0.00)
	2	0.16	0.70	0.14
		(0.01)	(0.01)	(0.01)
	3	0.02	0.14	0.84
		(0.00)	(0.01)	(0.01)

(e) Chemicals

		at $t+1$		
		1	2	3
Tercile at t	1	0.84	0.15	0.01
		(0.01)	(0.01)	(0.00)
	2	0.23	0.65	0.12
		(0.02)	(0.02)	(0.01)
	3	0.02	0.19	0.79
		(0.00)	(0.01)	(0.02)

(f) Machinery Eq

Table B5: Transition Matrices of MRPK, by Industry.

Notes: The tables report the estimated transition probabilities for terciles of the MRPK distribution for each of the 2-digit industries in our analysis. Bootstrapped standard errors in parentheses.

B.3.4 MRPK Autocorrelation

We also estimate the heterogeneity in persistence by MRPK tercile in a linear specification. In particular, we estimate the following autocorrelation specification:

$$\log(MRPK_{jnt}) = \alpha + \sum_{q\in\{1,2,3\}} (\rho_q \log(MRPK_{jnt-1}) \times \mathcal{I}_{jn,t-1,q}) + \gamma_n + \gamma_t + \epsilon_{jnt} \quad \text{(B1)}$$

where $\log(MRPK_{jnt})$ refers to the log of the MRPK measure for firm j in industry n at time t and $\mathcal{I}_{jn,t-1,q}$ is a dummy variable that takes value 1 if firm j in industry n belong to tercile q of the MRPK distribution at time $t-1$. γ_n is an industry fixed effect, and γ_t is a year fixed effect.

Table B6 reports our findings. The first row considers a pooled autocorrelation regression (with no heterogeneous effect by MRPK tercile), while the other rows show the autocorrelation coefficients for each tercile of the MRPK distribution. The first column reports our baseline estimates from equation (B1). In the second column, we verify that the property of asymmetric persistence of MRPK survives the inclusion of firm fixed effects. Specifically, we let the autocorrelation coefficient be different depending on the current state and find that the low MRPK states are associated with higher persistence, both when we include and when we do not include firm fixed effects.

Unsurprisingly, the estimated levels of autocorrelation decrease in the presence of fixed effects, because the fixed effects capture a degree of persistence. In our empirical setting, distinguishing between a highly persistent (but mean-reverting) component and a fully permanent component of firm-level MRPK is challenging, because this analysis would require a long sample for a given firm, and the attrition rate from the EEA survey that we use to measure capital is relatively high.

B.4 Employment Subsidies or State-Owned Enterprises

We now discuss some alternative explanations for our findings on MRPK mobility.

A possible driver of asymmetric MRPK persistence is the presence of employment subsidies for large firms; this type of distortion might lead poorly performing firms to remain large. Figure B3 below reports the marginal effect of employment on tail persistence, that is, the likelihood of staying in the same tercile. Larger firms in the first tercile are in fact more likely to switch out of the first tercile (relative to large firms in the third tercile), suggesting that employment subsidies are unlikely to explain our findings.

	MRPK	MRPK (Firm FE)
ρ	0.781	0.169
	(0.022)	(0.056)
ρ_{MRPK_1}	0.841	0.266
	(0.012)	(0.037)
ρ_{MRPK_2}	0.825	0.229
	(0.016)	(0.042)
ρ_{MRPK_3}	0.624	0.009
	(0.058)	(0.076)

Table B6: MRPK Persistence and Fixed Effects

Notes: The table reports our estimates for the vector of coefficients ρ, in equation (B1). The first column reports our baseline estimation. The second column includes firm fixed effects. The number of observations is 6,156. Standard errors, clustered at the firm-level, are in parentheses.

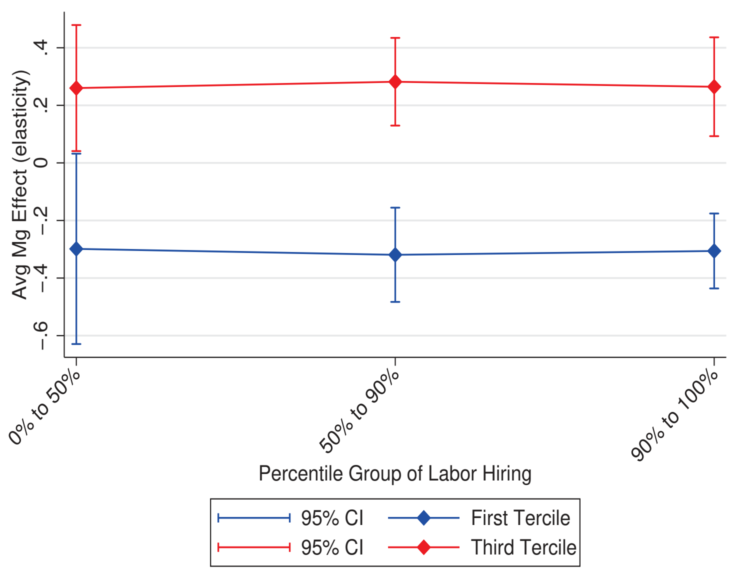


Figure B3: Effect of Firm Size by Employment on Tail Persistence.

Notes: This figure shows the elasticity of the probability of staying in the same tercile of MRPK with respect to employment, by firm size. Circles represent probability of staying conditional on being on the first tercile, and diamonds conditional on being on the third tercile of MRPK distribution. Confidence intervals are shown at the 95% significance.

Moreover, state-owned firms could also be subsidized to remain large and survive in the market. However, there are no state-owned enterprises in the six industries we use in our analysis.

B.5 Variance Decomposition of MRPK Changes

We now provide further evidence that the asymmetric persistence of MRPK is driven by a small disinvestment response to negative profitability shocks. We do this with a variance decomposition approach. Recall that under our assumptions,

$$\log MRPK_t = \log(\alpha\theta) - \log(k_t) + \log(p_t y_t) \tag{B2}$$

$$\implies \log(\frac{MRPK_{t+1}}{MRPK_t}) = \log(\frac{k_{t+1}}{k_t}) + \log(\frac{p_{t+1}y_{t+1}}{p_t y_t}) \tag{B3}$$

$$\implies var(\log(\frac{MRPK_{t+1}}{MRPK_t})) = var(\log(\frac{k_{t+1}}{k_t})) + var(\log(\frac{p_{t+1}y_{t+1}}{p_t y_t})) + cov(\log(\frac{k_{t+1}}{k_t}), \log(\frac{p_{t+1}y_{t+1}}{p_t y_t})) \tag{B4}$$

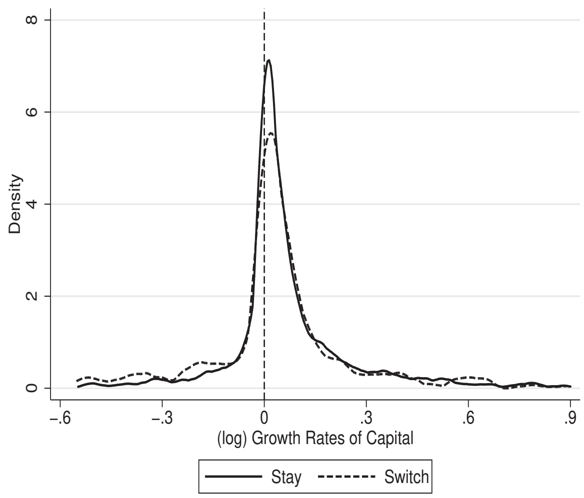
The growth rate of MRPK can be decomposed into a component that comes from the choice of capital (i.e. k_{t+1}), and a component that arises from a shock to value added in the following period (i.e. $p_{t+1}y_{t+1}$). This decomposition is reflected in Table B7. Moreover, this also implies that mechanically, the probability that a firm stays in a current quantile is a combination of the change in the firm's capital stock and the shock to profitability in the next period.

	First Tercile	Third Tercile
$var(\log(\frac{k_{t+1}}{k_t})))$	0.14	0.86
$var(\log(\frac{p_{t+1}y_{t+1}}{p_t y_t}))$	0.46	0.46
$cov(\log(\frac{k_{t+1}}{k_t}), \log(\frac{p_{t+1}y_{t+1}}{p_t y_t}))$	0.06	-0.11

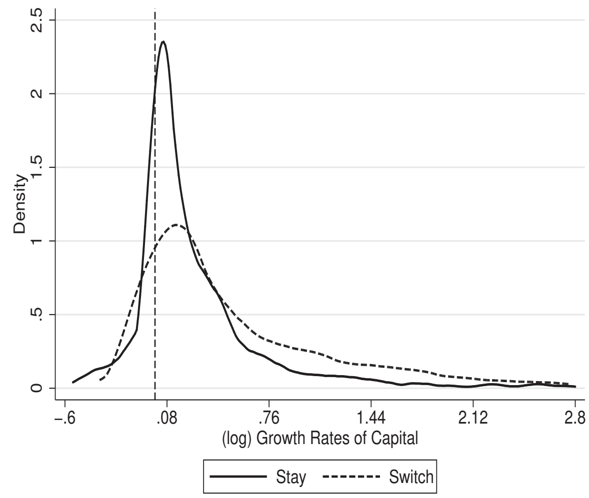
Table B7: Variance Decomposition of Growth Rate of MRPK

Given the decomposition above, we see that for firms in the first tercile, the majority of the variation in MRPK is driven by shocks to value added (almost 80% when we ignore the contribution of the covariance term). This fact suggests that when firms in the first tercile switch out of their ranks, they do so not because they are downsizing; instead, they receive higher productivity draws in the following period.

This result is also reflected in Figures B4 and B5, where we plot the kernel density estimates of the growth rates of capital and ω for firms that stayed in their current tercile, or switched out of their current tercile. For low-MRPK firms, we see in Panel (a) of Figure B4 that there is almost no difference in the distribution of capital growth rates for firms that switched or stayed; however, their draws of future productivity are distinctly different, as reflected in Panel (a) of Figure B5. For high MRPK firms, Panel (b) of Figures B4 and B5, we see that the firms that switch out generally have higher growth rates of capital, and lower ω growth rates.



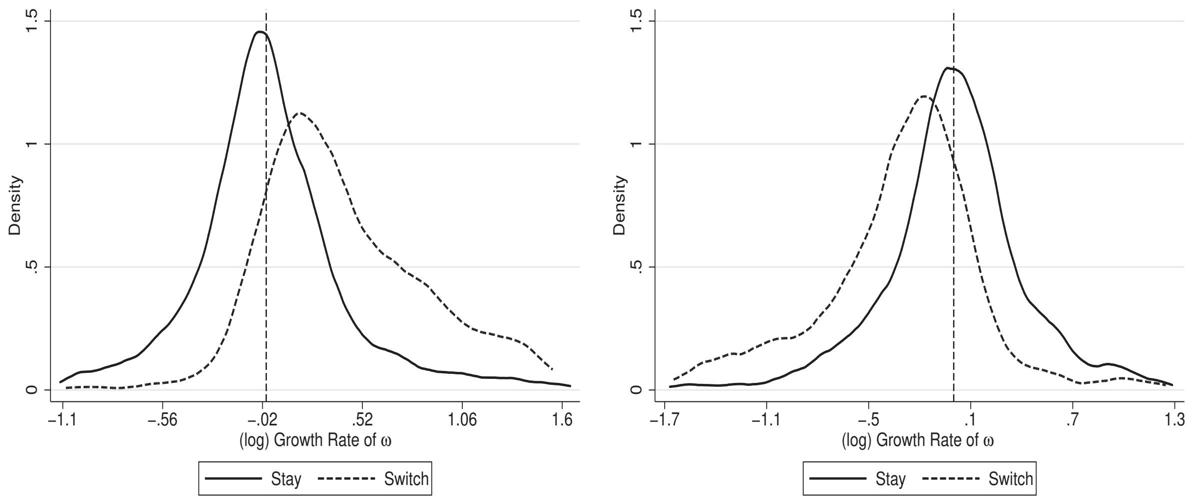
(a) First Tercile



(b) Third Tercile

Figure B4: Distribution of $\log(\frac{k_{t+1}}{k_t})$ for First and Third Terciles.

*Notes:*The figure shows the estimated kernel density of (log) growth rates of capital for firms in the first- and third-tercile of the MRPK distribution. Solid lines represent the growth rates of those who stay in the same tercile next year, while dashed lines refer to capital growth rate of firms switching terciles. Dashed black vertical line refers to the mean of the distribution.



(a) First Tercile

(b) Third Tercile

Figure B5: Distribution of $\log(\frac{\omega_{t+1}}{\omega_t})$ for First and Third Terciles

Notes: This figure shows the estimated kernel density of (log) growth rates of ω for firms in the first- and third-tercile of the MRPK distribution. Solid lines represent the growth rates of those who stay in the same tercile next year, while dashed lines refer to ω growth rate of firms switching terciles. Dashed black vertical line refers to the mean of the distribution.

B.6 Capital Predicts Survival

Figure B6 shows the contours of the probability of firm survival, with (log) capital on the x-axis and (log) ω on the y-axis, based on our estimates for equation (18). The figure shows that a firm's survival probability depends positively on both productivity and level of capital. Accordingly, the isoprobability curves are downward sloping.

Table B8 shows the point estimates and standard errors for equation (18). The first column shows the results for our full sample, where the estimates correspond to Figure B6. The second column refers to the same regression only with data for the years after 2007. In all cases, coefficients for ω_{jnt} and capital stock are positive and highly significant, leading to a downward sloping isoprobability line for survival.

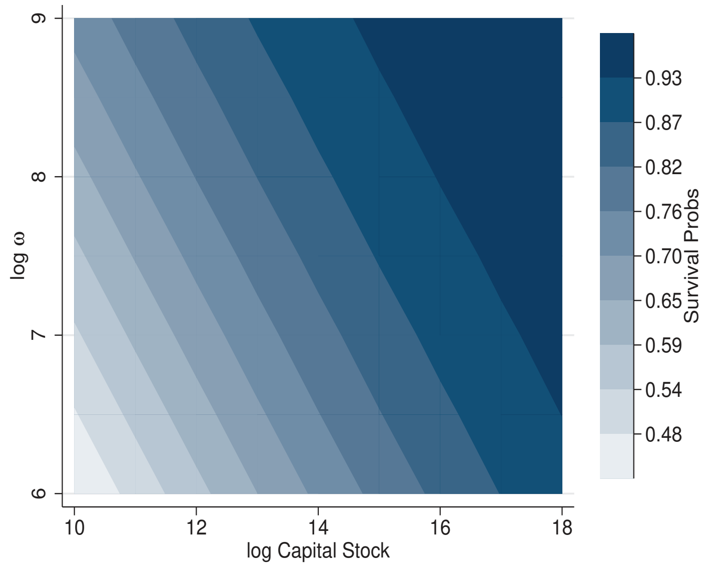


Figure B6: Selection Effects of Productivity and Capital.

Notes: The figure displays a heat map of survival probabilities as a function of (log) capital stock on the x-axis and (log) productivity (ω) on the y-axis. Darker colors denote higher survival probabilities.

	Probability of Survival	
	Full Sample	Post 2007 Sample
$\log(\omega_{jnt})$	0.285	0.335
	(0.018)	(0.028)
$\log(k_{jnt})$	0.207	0.252
	(0.008)	(0.012)

Table B8: Effect of Trade Shock on Survival.

Notes: The table reports our estimates for β_1 (first row) and β_2 (second row), in equation (18). The first column refers to the full sample with the corrected measure of exit (the number of observations is 12,401); the second column refers to the sample only considering the period post-2007 (the number of observations is 7,403). Given there is not a large variation within a 4-digit industry, we use 2-digit industry fixed effect in the post-2007 regression to control for permanent differences in survival rates by industry. In all specifications, standard errors, clustered at the firm-level, are in parentheses.

B.7 Capital Composition, Depreciation and Selection

We estimate the following specification,

$$\begin{aligned} Survival_{jnt,t+1} &= \begin{cases} 1 & \text{if} \quad z^*_{jnt} > 0 \\ 0 & \text{otherwise} \end{cases} \\ z^*_{jnt} &= \beta_0 + \beta_1 \log(\omega_{jnt}) + \beta_2 \log(k_{jnt}) + \beta_3 \delta_{jnt} + \beta_4 \log(\omega_{jnt}) * \delta_{jnt} \\ &\quad + \beta_5 \log(k_{jnt}) * \delta_{jnt} + \gamma_n + \gamma_t + \epsilon_{jnt} \end{aligned} \tag{B5}$$

with the results presented in Table B9. Firms with higher firm-level depretiation rates have a lower marginal effect of capital on survival, consistent with the presence of capital irreversibility frictions. To see this more clearly, the average marginal effect of capital level on the probability of survival is plotted in Figure B7.

	Prob Survival
$\log(\omega_{jnt})$	0.281
	(0.047)
$\log(\mathrm{k}_{jnt})$	0.237
	(0.023)
δ_{jnt}	3.728
	(4.275)
$\log(\omega_{jnt}) * \delta_{jnt}$	-0.026
	(0.391)
$\log(\mathrm{k}_{jnt}) * \delta_{jnt}$	-0.215
	(0.195)

Table B9: The Effect of Capital on Survival by Depreciation Rates.

Notes: The table reports our estimates for the vector of β, in equation (B5). The number of observations is 12,401. Standard errors, clustered at the firm-level, are in parentheses.

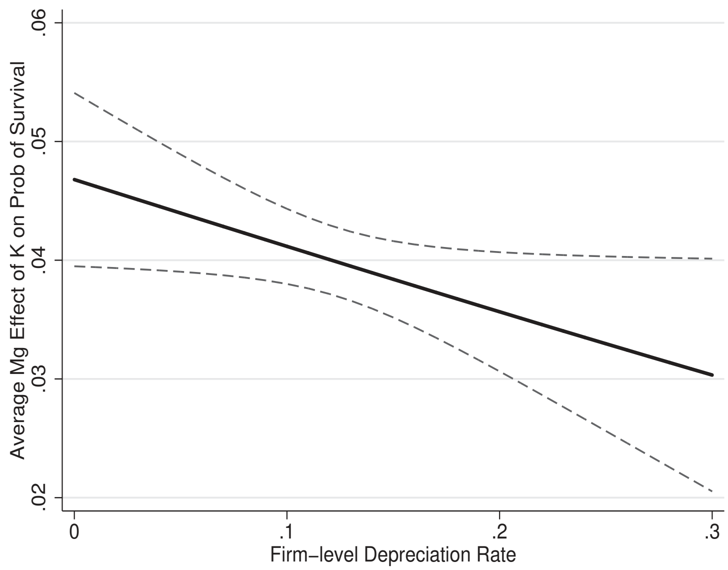


Figure B7: The Effect of Capital on Survival by Depreciation Rates.

Notes: The figure shows the average marginal effect of k_{jnt} on the probability of survival for firms with bundles of capital of different depreciation rates.

B.8 Labor Reallocation

To complement our analysis of capital reallocation, we also analyze the properties of labor reallocation. First, we compute the standard deviation of the (log) marginal revenue product of labor (MRPN). When we consider the whole sample and residualize MRPN using industry and time fixed effects, this standard deviation equals 0.88. When we consider each industry separately, we find values in the range (0.69, 0.99). Thus, consistent with the literature, we find that returns from labor are substantially less dispersed than returns from capital.

Next, we study the mobility of MRPN using the same methodology we described for MRPK. We construct terciles of MRPN for each industry and year and estimate the transition probabilities across these terciles. In Table B10, we report the estimated transition matrix for the whole sample. We find evidence of the persistence of MRPN (i.e., higher probabilities on the diagonal of the transition matrix). However, we do not find evidence of asymmetric persistence, different from our key finding about the dynamics of MRPK.

Taken together, these results suggest that firms face smaller frictions in the reallocation of labor than in the reallocation of capital, and the frictions that affect labor adjustment do not display asymmetry with respect to positive or negative profitability shocks. Thus, in the paper we focus our attention on the role of capital-reallocation frictions after import-competition shocks.

		at $t+1$ 1	2	3
Tercile at t	1	0.71	0.23	0.06
		(0.01)	(0.01)	(0.00)
	2	0.25	0.59	0.17
		(0.00)	(0.01)	(0.00)
	3	0.07	0.24	0.69
		(0.00)	(0.01)	(0.01)

Table B10: Transition Probabilities of MRPN.

Notes: The table reports the estimated transition probabilities for terciles of the MRPN distribution. Bootstrapped standard errors in parentheses.

C Capital Composition, Depreciation, and Utilization

In this appendix, we combine a model and data to analyze the role of heterogeneous capital goods for the dynamics of MRPK. We also analyze the empirical patterns of capital utilization in our data.

C.1 Model with Capital Heterogeneity in Depreciation and Irreversibility

We now describe a simplified model with two types of capital, that are potentially heterogeneous in their depreciation rates and in their degree of irreversibility. We use this model to provide a foundation for our empirical analysis that exploits the heterogeneous capital composition across firms to emphasize the importance of investment irreversibility.

Consider the following technology:

$$y_t = s_t k_t^{\alpha}, \tag{C1}$$

$$k_t = k_{1t}^{\phi} k_{2t}^{1-\phi}, \tag{C2}$$

where the parameter $\alpha \in (0, 1)$ captures the overall degree of returns-to-scale, potentially combining both technological and demand factors, and s_t is productivity. Firms produce output y_t with a decreasing-returns-to-scale production function, using a Cobb-Douglas aggregator k_t of two types of capital k_{1t} and k_{2t}. For simplicity we abstract from labor, but it would be straightforward to add a static input without affecting any insights.

These two types of capital may differ in two respects. First, they may have different rates of depreciation, giving the following capital accumulation equations:

$$k_{j,t+1} = k_{jt}(1 - \delta_j) + i_{jt}, \tag{C3}$$

where i_{jt} is investment, for $j = 1, 2$.

Second, the two types of capital may have different degrees of irreversibility. For simplicity, we assume that each capital type is either fully irreversible or fully reversible, and denote by $\mathcal{I}_j^{irr}$ an indicator function that equals one if capital type j is irreversible and zero otherwise. We can thus express the irreversibility constraints as follows:

$$\mathcal{I}_j^{irr} i_{jt} \geq 0, \tag{C4}$$

for $j = 1, 2$.

The firm solves the following maximization problem:

$$\max_{\{i_{1t},i_{2t},k_{1,t+1},k_{2,t+1}\}} \sum_{t=0}^{\infty} \beta^t \left(y_t - i_{1t} - i_{2t}\right), \tag{C5}$$

where we have set the price of both capital goods to equal one, subject to the technological constraints specified above.

For simplicity and expositional purpose, we assume that productivity is constant $s_t = 1$ and then consider an unexpected shock that leads to a different, permanent level. We focus on two cases. First, we consider heterogeneity in depreciation rates. Second, we consider heterogeneity in irreversibility.

Case 1: Heterogeneous Depreciation. We now analyze the role of heterogeneity in depreciation rates for the dynamics of the marginal product of capital. We obtain the following prediction, that we test in our data: Firms that operate a capital with lower average depreciation rate display more persistence in the marginal product, when the marginal product is relatively low.

To obtain a stark characterization, we assume that k_{1t} has depreciation rate $\delta_1 \in (0, 1)$, whereas k_{2t} fully depreciates in one period, i.e., $\delta_2 = 1$. The numerical results can be easily extended to the more general case $0 < \delta_1 < \delta_2 \leq 1$.

We assume that both types of capital are subject to the irreversibility constraint (C4): $\mathcal{I}_1^{irr} = \mathcal{I}_2^{irr} = 1$. However, notice that, because of full depreciation, the irreversibility constraint never binds for $j = 2$. To see this, set $i_{2t} = 0$; this gives $k_{2,t+1} = 0$, which is never optimal because the production function satisfies an Inada condition. Thus, optimal investment is always interior for capital k_{2t}.

Thus, we can express the optimality conditions for investment as follows:

$$1 - \lambda_{1t} = \beta\left(\alpha\phi s_{t+1} k_{t+1}^{\alpha-1} k_{1,t+1}^{\phi-1} k_{2,t+1}^{1-\phi} + (1-\delta_1)(1-\lambda_{1,t+1})\right), \tag{C6}$$

$$1 = \beta\alpha(1-\phi) s_{t+1} k_{t+1}^{\alpha-1} k_{1,t+1}^{\phi} k_{2,t+1}^{-\phi}, \tag{C7}$$

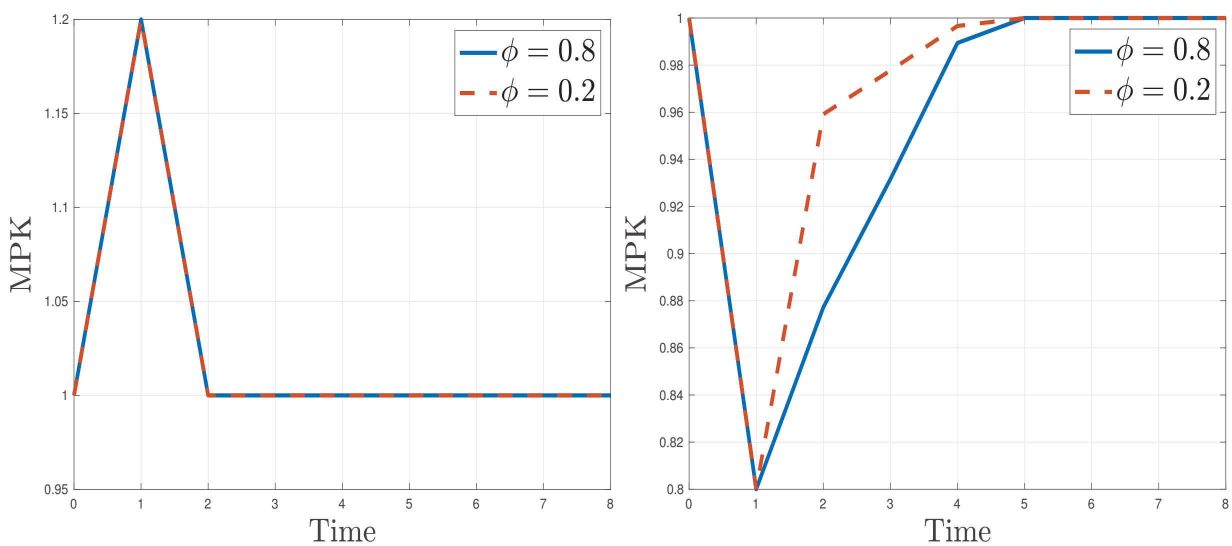
with complementary slackness $\lambda_{1t} i_{1t} = 0$, where λ_{1t} is the Lagrange multiplier on the irreversibility constraint (C4) for $j = 1$.

We now consider a numerical illustration of the mechanism and report the parameter values in the notes to the figures below. In particular, we impose that at $t = 0$ the firm is at its steady state associated with constant productivity $s_t = 1$. Then, at $t = 1$, productivity unexpectedly drops to a permanent level $s < 1$. We assume the shock is sufficiently large that the irreversibility constraint binds for some time before the firm reaches its new steady state. Thus, for several periods, we have $k_{1,t+1} = (1 - \delta_1)k_{1t}$, and plugging this into (C7) we can obtain the optimal choice for $k_{2,t+1}$.

We consider two firms, which are heterogeneous in the technological parameter ϕ. The first firm has a high value of ϕ, whereas the second firm has a low value. As a result, the first firm has a capital stock that on average depreciates at a lower rate than the second firm. For each firm, we measure the marginal product of capital $\alpha\frac{y_t}{k_t}$ and we display it in Figure C1, where the solid line refers to the firm with high ϕ and the dashed line refers to the firm with low ϕ. The left panel refers to a permanent increase in productivity, whereas the right panel refers to a permanent decrease.

Following a positive shock, the marginal product of both firms jumps on impact, and then immediately returns to its steady-state value, because there is no friction in adjusting capital upwards: Because of the simplifying assumption that productivity is deterministic, there is no wait-and-see effect from *future* occasionally binding irreversibility.

Following a negative shock, the marginal product declines persistently because of irreversibility of investment. Critically, this persistence is larger for the firm with a larger share of slowly depreciating capital (high ϕ).



(a) Positive Shock (b) Negative Shock

Figure C1: Heterogeneous Depreciation and MRPK Persistence.

Notes: The figure displays the path of the marginal product of capital after an unexpected, permanent productivity shock (positive in the left panel, negative in the right panel), for a firm with high ϕ (solide line) and a firm with low ϕ (dashed line). Parameter values: $\alpha = \frac{1}{3}$; $\beta = 0.96$; $\delta_1 = 0.1$; $\phi \in \{0.2, 0.8\}$; $s_t \in \{0.8, 1.2\}$ for $t \geq 1$.

Case 2: Heterogeneous Irreversibility. We now analyze the role of heterogeneity in the degree of investment irreversibility for the dynamics of the marginal product of capital. We derive the following prediction, that we test in the data: The persistence of low marginal products of capital is accounted for by more irreversible types of capital.

To obtain a stark characterization, we assume that the first type of capital is fully irreversible, whereas the second type is fully reversible, i.e., $\mathcal{I}_1(irr) = 1$, $\mathcal{I}_2(irr) = 0$. We further assume that the depreciation rate is homogeneous across the two capital goods, i.e., $\delta_1 = \delta_2 = \delta \in (0, 1)$.

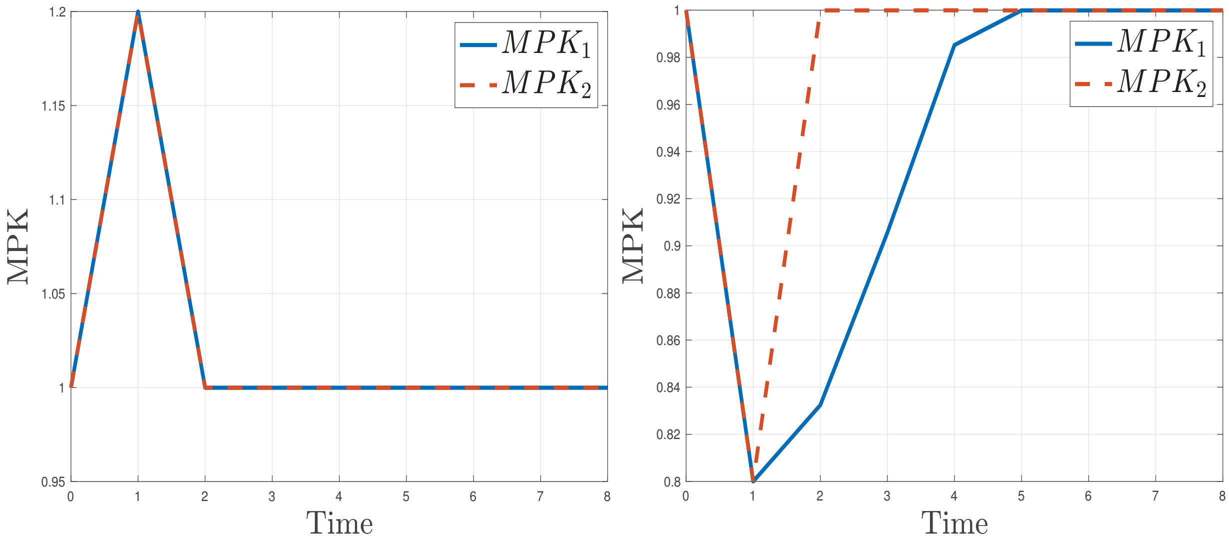
In this case, we can express the optimality conditions of the firm as follows:

$$1 - \lambda_{1t} = \beta \left(\alpha\phi s_{t+1} k_{t+1}^{\alpha-1} k_{1,t+1}^{\phi-1} k_{2,t+1}^{1-\phi} + (1-\delta)(1-\lambda_{1,t+1}) \right), \tag{C8}$$

$$1 = \beta \left(\alpha(1-\phi) s_{t+1} k_{t+1}^{\alpha-1} k_{1,t+1}^{\phi} k_{2,t+1}^{-\phi} + (1-\delta) \right), \tag{C9}$$

with complementary slackness $\lambda_{1t} i_{1t} = 0$, where λ_{1t} is the Lagrange multiplier on the irreversibility constraint (C4) for $j = 1$.

As in the case of heterogeneous depreciation rates, we consider both a positive and a negative permanent shock to productivity, hitting a firm in its steady state associated with $s_t = 1$. In Figure C2, we display the associated path of the average products of the two types of capital. We find that in response to a negative shock, the average product of the irreversible type of capital remains persistently low, whereas the reversible type of capital displays less persistence. No persistence (nor, clearly, difference in persistence) across the two types of capital arises in the case of a positive shock.



(a) Positive Shock (b) Negative Shock

Figure C2: Heterogeneous Irreversibility and MRPK Persistence.

Notes: The figure displays the path of the average product of the irreversible capital (solid line) and the reversible capital (dashed line) foll (positive in the left panel, negative in the right panel) after an unexpected, permanent productivity shock (positive in the left panel, negative in the right panel). Parameter values: $\alpha = \frac{1}{3}$; $\beta = 0.96$; $\delta = 0.1$; $\phi = 0.5$; $s_t \in \{0.8, 1.2\}$ for $t \geq 1$.

C.2 Capital Composition, Depreciation, and MRPK Mobility

We now test empirically the predictions of the model. First, we explore the role of heterogeneous depreciation by examining the impact of firm-level depreciation rates on the probability of staying in the same tercile of the MRPK distribution.

We analyze the impact of capital depreciation rates on the persistence of a firms' MRPKs by estimating the following probit model:

$$\mathcal{I}_{jnt}\left(q' = q\right) = \begin{cases} 0 & \text{if } Y_{jnt} < 0 \\ 1 & \text{if } Y_{jnt} \geq 0 \end{cases}$$

$$Y_{jnt} = a + \eta\delta_{jnt} + \theta X_{jt} + \gamma_n + \gamma_t + \epsilon_{jnt} \tag{C10}$$

where $\mathcal{I}_{jnt}\left(q' = q\right)$ is an indicator function that takes a value of one if firm j is in tercile q of the MRPK distribution of industry n in year t and remains in the same tercile in year $t+1$, η is our coefficient of interest, mapping firm-level depreciation rates into the probability of staying in the same rank of MRPK, X_{jt} are firm-level controls (e.g., capital level and value added), γ_n is an industry fixed effect, and γ_t is a year fixed effect.

We first focus on firms in the first tercile of the MRPK distribution, i.e., low-MRPK firms which are more likely to be directly affected by capital resale frictions. We find a statistically significant negative effect of depreciation rates on the persistence of MRPK, meaning that a higher depreciation rate makes it more likely that a firm with currently low MRPK will move to a tercile associated with higher MRPK in the following year. The estimated effect implies that a 1% increase in the firm-level depreciation rate decreases the probability of staying in the first tercile of the MRPK distribution by 0.15% on average. This effect is larger than relative to other terciles.

	Prob. Staying in Same Tercile	
	First Tercile	Third Tercile
δ_{jnt}	-5.087	3.048
	(1.496)	(1.223)

Table C1: The Effect of Depreciation Rates on the Persistence of Low MRPKs.

Notes: The table reports our estimates for the vector of η, in equation (C10). The number of observations is 2,013. Standard errors, clustered at the firm-level, are in parentheses.

Second, we examine whether a particular type of capital drives the asymmetric persistence of the MRPK distribution. To this end, we construct marginal revenue product measures for every type of capital and estimate their autocorrelation, allowing for heterogeneity by initial tercile.

To examine what type of capital drives the left tail persistence of the MRPK distribution, we estimate the following autocorrelation specification,

$$\log(MRPK_{jnt}) = \alpha + \sum_{q\in\{1,2,3\}} (\rho_q \log(MRPK_{jn,t-1}) \times \mathcal{I}_{jn,t-1,q}) + \gamma_n + \gamma_t + \epsilon_{jnt} \quad \text{(C11)}$$

where $\log(MRPK_{jnt})$ refers to the log of the MRPK measure for firm j in industry n at time t, constructed using as a proxy for capital a particular type of fixed asset (e.g., machinery or computational equipment), and $\mathcal{I}_{jnt-1,q}$ is a dummy variable that takes value 1 if firm j in industry t belong to tercile q of the MRPK distribution at time $t-1$. γ_j is an industry fixed effect, and γ_t is a year fixed effect.

Table C2 shows the autocorrelation coefficients for two separate specifications. The first row refers to the pooled autocorrelation, while the second to fourth display the heterogenous effects.

	Buildings and Fixed Instalations	Machinery	Transport Units	IT Equipment	Furniture
ρ	0.745	0.765	0.763	0.724	0.783
(no interaction)	(0.018)	(0.025)	(0.035)	(0.031)	(0.019)
ρ_{MRPK_1}	0.847	0.813	0.247	0.294	0.400
	(0.027)	(0.026)	(0.056)	(0.066)	(0.036)
ρ_{MRPK_2}	0.201	0.506	0.564	0.567	0.675
	(0.023)	(0.046)	(0.057)	(0.047)	(0.023)
ρ_{MRPK_3}	0.783	0.758	0.830	0.714	0.782
	(0.021)	(0.024)	(0.029)	(0.032)	(0.019)

Table C2: Autocorrelation of MPRK by Capital Type.

Notes: The table reports our estimates for the vector of coefficients ρ, in equation (C11). The first column considers only the type of capital defined as buildings and fixed instalations (the number of observations is 4,292). The second column refers to machinery and equipment (the number of observations is 5,797). The third column refers to transportation units (the number of observations is 4,936). The fourth column refers to computational and IT equipment (the number of observations is 2,368). Finally, the fifth column refers to furniture (the number of observations is 5,476). Standard errors, clustered at the firm-level, are in parentheses.

Notably, the marginal revenue product of fixed installations and machinery features a significantly higher persistence for firms in the lowest tercile. This result is consistent with the notion that these types of capital have a higher degree of firm specificity and thus irreversibility.

C.3 Capital Utilization

We now consider the margin of capital utilization. We find that firms with low MRPK tend to underutilize their capital, consistent with the presence of frictions that make it costly to downsize in response to negative profitability shocks. To measure capital utilization, we use data on firms' expenditures on energy. Assuming energy is complementary to the amount of capital used in production (at least in the short run), we measure the utilization rate as the ratio of energy inputs to capital stock. We then recompute firms' MRPK using utilized capital instead of total capital stock. This analysis can be also be rationalized as a special case of the model described above with two types of (capital) inputs, where energy is a more flexible (less irreversible) input.

Two findings suggest that utilization is an important channel, especially for firms with low MRPK. We first find that after adjusting for utilization, the cross-sectional dispersion of MRPK decreases for most industries and years. Second, the high relative persistence of low returns (relative to high returns) disappears once MRPK is adjusted for utilization.[43] We cannot reject that the probability of remaining in the lowest tercile equals the probability of staying in the highest tercile when we correct MRPKs for utilization. Firms hit by negative profitability shocks do not downsize, but hold their capital and decrease the intensity of utilization. Hence, their measured MRPK—based only on the size of the capital stock—remains persistently low, whereas their adjusted MRPK—which accounts for energy consumption—increases faster, as the effective capital input shrinks through underutilization.

To compute utilization rates, we use data on firms' expenditures on energy, e_{it}. For simplicity, we assume that energy is complementary to the amount of capital used in production and measure the utilization rate u_{it} of capital as the ratio of energy inputs to capital stock, that is, $u_{it} = \frac{e_{it}}{k_{it}}$. We then recompute firms MRPK using utilized capital $u_{it}k_{it}$ as capital input instead of k_{it}. Then, we estimate the following autocorrelation specification with the corrected measure of MRPK.

$$\log(MRPK_{jnt}) = \alpha + \sum_{q \in \{1,2,3\}} (\rho_q \log(MRPK_{jnt-1}) \times \mathcal{I}_{jnt-1,q}) + \gamma_n + \gamma_t + \epsilon_{jnt} \quad \text{(C12)}$$

where $\log(MRPK_{jnt})$ refers to the log of the MRPK measure for firm j in industry n at time t, corrected and uncorrected with utilization, and $\mathcal{I}_{jnt-1,q}$ is a dummy variable that takes value 1 if firm j in industry n belongs to tercile q of the MRPK distribution at time $t-1$. γ_n is an industry fixed effect, and γ_t is a year fixed effect.

Table C3 shows the results with the corrected measure (first column), and our baseline MRPK (second column). The first row refers to the autocorrelation coefficient in a pooled specification, while the second to fourth display the heterogeneous effects.

[43]Table C3 in Appendix C.3 reports the autocorrelation of MRPK, both unconditional and conditional on the current tercile of MRPK after the utilization adjustment, and compares to baseline estimates. We also perform this analysis using materials to proxy for utilization and find similar results.

Variables	MPRK (utilization adjusted)	MRPK
ρ (no interaction)	0.703	0.781
	(0.022)	(0.022)
ρ_1 (1st tercile MRPK)	0.584	0.841
	(0.048)	(0.012)
ρ_2 (2nd tercile MRPK)	0.684	0.825
	(0.028)	(0.016)
ρ_3 (3rd tercile MRPK)	0.695	0.624
	(0.022)	(0.058)

Table C3: Persistence of MRPK and Capital Utilization.

Notes: The table reports our estimates for the vector of coefficients ρ, in equation (C12). The measure of MRPK adjusted by utilization uses energy as a proxy for utilization. The number of observations is 6,076 for the first column and 6,156 for the second column. Standard errors, clustered at the firm-level, are in parentheses.

We also compute the MRPK transition matrices by industry using the corrected measure of MRPK and we found no evidence of higher persitence on the first tercile.

		at $t+1$		
		1	2	3
Tercile at t	1	0.72	0.23	0.06
		(0.02)	(0.01)	(0.01)
	2	0.16	0.64	0.20
		(0.01)	(0.02)	(0.01)
	3	0.05	0.18	0.77
		(0.01)	(0.01)	(0.01)

(a) Food

		at $t+1$		
		1	2	3
Tercile at t	1	0.79	0.17	0.03
		(0.01)	(0.01)	(0.00)
	2	0.21	0.70	0.08
		(0.01)	(0.01)	(0.01)
	3	0.04	0.17	0.79
		(0.01)	(0.01)	(0.01)

(b) Textiles

		at $t+1$		
		1	2	3
Tercile at t	1	0.72	0.21	0.07
		(0.02)	(0.01)	(0.01)
	2	0.17	0.61	0.22
		(0.01)	(0.01)	(0.01)
	3	0.05	0.23	0.72
		(0.01)	(0.01)	(0.01)

(c) Apparel

		at $t+1$		
		1	2	3
Tercile at t	1	0.70	0.25	0.05
		(0.02)	(0.02)	(0.01)
	2	0.25	0.58	0.18
		(0.01)	(0.01)	(0.01)
	3	0.05	0.21	0.74
		(0.01)	(0.01)	(0.01)

(d) Printing

		at $t+1$		
		1	2	3
Tercile at t	1	0.85	0.11	0.04
		(0.01)	(0.01)	(0.01)
	2	0.12	0.77	0.11
		(0.01)	(0.01)	(0.01)
	3	0.03	0.13	0.83
		(0.00)	(0.01)	(0.01)

(e) Chemicals

		at $t+1$		
		1	2	3
Tercile at t	1	0.78	0.18	0.04
		(0.02)	(0.02)	(0.01)
	2	0.17	0.62	0.20
		(0.01)	(0.02)	(0.01)
	3	0.05	0.22	0.74
		(0.01)	(0.02)	(0.02)

(f) Machinery Eq

Table C4: Transition Matrices of Utilization Correction MRPK, by Industry.

Notes: The tables report the estimated transition probabilities for terciles of the adjusted MRPK distribution for each of the 2-digit industries in our analysis. Bootstrapped standard errors in parentheses.

D Quantitative Model

In this appendix, we provide additional details and results from our quantitative model.

D.1 Definition of Recursive Stationary Equilibrium

For simplicity of notation, we assume the state space is discrete. In a stationary equilibrium, the aggregate state Z is constant. Given exogenous probability distributions (idiosyncratic productivity transition $F(s, s')$ and operation cost $G(f; s)$), a **recursive stationary equilibrium** is defined as:

- Household's decision for consumption C and labor N;
- Value functions:
$$V(k, s, f), V^c(k, s, f), V^x(k, s);$$
- Firms' decision rules: entry $e(s^e, f) \in \{0, 1\}$, initial capital for entrants $k' = g^e(s^e)$, future capital for continuing firms $k' = g(k, s)$, exit $x(k, s, f) \in \{0, 1\}$, labor demand $n(k, s)$;
- Aggregate price index P;
- Employment N^X and output X in the commodity sector;
- Equilibrium distributions: producing firms $\lambda(k, s)$, continuing firms $\mu(k, s)$; total measure of producing firms $M = \sum_k \sum_s \lambda(k, s)$;

such that

- Household's decision rules satisfy the first order condition for labor supply;
- Firms' value functions and decision rules solve the dynamic program (10), (11), (12), (13);
- Output market and labor market clear, that is

$$C = \left(\sum_k \sum_s (s k^{\alpha} n(k, s)^{1-\alpha})^{\theta} \lambda(k, s) \right)^{\frac{1}{\theta}} \tag{D1}$$

$$N = \sum_k \sum_s n(k, s) \lambda(k, s) + N^X + \bar{f}^e + \bar{f} + \bar{\gamma}; \tag{D2}$$

where $\bar{f}^e$ and $\bar{f}$ are the aggregate levels of labor inputs employed to pay for entry and continuation costs respectively, and $\bar{\gamma}$ is the aggregate level of labor employed to pay for the convex adjustment cost.

- The value of imports, i.e. aggregate domestic investment, equals the value of exports, i.e. commodity output;

$$\sum_k \sum_s Q(i(k,s))i(k,s)\lambda(k,s) = p^X X; \tag{D3}$$

where the marginal cost of investment is Q for firms doing positive investment, q for continuing firms doing negative investment, and $(1-\zeta)q$ for exiting firms.

- The equilibrium distributions satisfy

$$\mu(k,s) = \sum_k \sum_s \sum_f \lambda(k,s)G(f;s)\left(1 - x(k,s,f)\right) \tag{D4}$$

$$\begin{aligned} \lambda(k',s') = &\sum_k \sum_s \mu(k,s)F(s,s')\mathcal{I}(k' = g(k,s)) \\ &+ M^P \sum_{s^e} \sum_f F^e(s^e)G(f;s^e)F(s^e,s')e(s^e,f)\mathcal{I}(k' = g^e(s^e)). \end{aligned} \tag{D5}$$

Notice that this definition also implies market-clearing in each manufacturing variety.

D.2 Calibration and Properties of Stationary Equilibrium

We now present several additional results that complement the analysis of the stationary equilibrium in Section 5.

Calibration. Table D1 reports the value of the moments targeted in our calibration in the data and in the baseline model. Because our calibration slightly underpredicts the high dispersion of revenue productivity in the data, we perform a robustness check with respect to the volatility of idiosyncratic shocks in Appendix D.8. Table D2 compares several aggregate variables in the baseline and the frictionless counterfactual model.

Moments	Data	Model
Freq of negative investment	0.108	0.111
Slope of exit thresholds	0.754	0.793
Autocorrelation of ω	0.742	0.753
Unconditional std dev of ω	0.848	0.753
Exit rate	0.184	0.171
Relative size at exit	0.345	0.366
Relative productivity at exit	0.757	0.713
Dispersion of $\frac{i}{k}$	0.828	0.857

Table D1: Calibration Targets.

Notes: The table reports the value of the targeted moments in the data and in the model.

Variable	BASELINE	FRICTIONLESS
C	1.40	1.70
K	2.08	2.82
N	0.41	0.39
M	1.56	1.32
TFP (average)	1.75	1.88
TFP	2.68	2.89
TFP^{Adj}	2.31	2.63

Table D2: Steady-state Comparison: Baseline and Frictionless Model.

Notes: The table reports several aggregate variables in the stationary equilibrium of the baseline model and in the stationary equilibrium of the frictionless model. Specifically: consumption, capital, labor, mass of active manufacturing firms, average firm-level productivity s, TFP (both unadjusted and adjusted for the number of varieties).

Responsiveness and Lumpiness of Investment. We now complement the discussion of investment responsiveness and lumpiness (Section 5.3). In Table D3 we report our estimates for the elasticity of investment with respect to MRPK. Specifically, we estimate the following regression equation:

$$\left(\frac{i}{k}\right)_{jnt} = \beta_0 + \beta_1 \log MRPK_{jnt} + \psi_j + \gamma_n + \delta_t + \epsilon_{jnt}, \tag{D6}$$

where the left-hand side reports the investment rate of firm j in industry n in year t and the right-hand side reports a constant, the marginal revenue product of capital—with our elasticity of interest β_1—as well as firm, industry, and year fixed effects, plus an error term.

	Data	Model	
		Baseline	Frictionless
$\log MRPK$	0.483	0.497	2.184
	(0.031)	(0.003)	(0.015)

Table D3: Elasticity of Investment Rate to MRPK.

Notes: The table reports our estimates for β_1 in regression equation (D6). The first column refers to our estimates in the data (the number of observations is 6,769)—standard errors clustered at the firm level are in parentheses. The second and third columns report the estimated coefficients in our baseline and the frictionless model, respectively (the number of observations is 92194 and 87880 respectively).

In Table D4, we consider a rich model with partial irreversibility, convex costs, and fixed adjustment costs proportional to the current capital stock, as in Cooper and Haltiwanger (2006), with coefficient f_k, so that firms pay a cost equal to $f_k Qk$ whenever their investment rate is different from zero. When we calibrate this model to match all our baseline moments plus the frequency of lumpy adjustments (absolute value of investment rate larger than 0.49), we obtain a parameter vector that is remarkably similar to our baseline calibration without a fixed cost. Consistent with this result, Table D5 reports that our baseline model closely matches the frequency of spikes.

Parameter	Baseline	Fixed Cost	Target / Source
ρ	0.759	0.759	Autocorrelation of ω
σ	0.790	0.790	Standard deviation of ω
q/Q	0.591	0.596	frequency of negative investment
ζ	0.176	0.170	Slope of exit thresholds
γ_0	0.001	0.001	Standard deviation of i/k
η_0	0.059	0.059	Exit rate
η_1	5.2010	5.2006	Relative size at exit
η_2	5.2025	5.2022	Relative productivity at exit
f_k	–	0.0008	$Pr\left(\lvert\frac{i}{k}\rvert > 0.49\right)$

Table D4: Parameter Values: Model with Fixed Adjustment Cost.

Notes: The table reports the calibrated parameter values in the baseline model and in the richer model with fixed adjustment costs.

Next, we analyze the timing of lumpy adjustments. Specifically, we define capital age as the time (in years) from the last spike episode to the last time we observe the firm in our sample. Table D5 shows these statistics for firms that only had one spike and for firms with at least one spike of investment. We also calculate the time between spikes conditional on firms having at least two investment spikes. In constructing all these statistics, we only consider firms that have been present in the sample for at least ten years. Since the data is not a balanced panel for all firms, we provide the statistics for two samples: (i) firms for which the difference between their last and initial year in the sample is greater or equal than ten years (Gaps) and (ii) firms that are observed for at least 10 consecutive years (No-Gaps). Overall, we find that the model is broadly consistent with these untargeted dimensions related to adjustment hazards.

Finally, we aim to assess the typical size of large adjustments in model and data. To this end, we consider an event study for investment rates, where the event is defined as the maximum investment rate for each firm in our dataset. We compute the average of this maximum across firms, and construct a 5-year window around the event, comparing investment behavior in model and data throughout this window. Both data and model show that investment spikes are typically surrounded by periods of relative inaction. Moreover, the average spike is of similar size in model and data, although the model appears to slightly overestimate the spike episode at the expenses of lower activity in the surrounding periods. We report our results in Figure D1, where we overlay our model predictions relative to the

		Data	Model
Uncond. Freq. of Spikes		0.195	0.225
	Data Gaps	Data No-Gaps	Model
Capital Age (only 1 spike)	5.310	6.000	5.537
Capital Age (cond at least 1 spike)	4.331	4.067	3.145
Avg. Time Gap till Adj. (cond. $\geq$ 2 spikes)	4.267	3.971	4.058

Table D5: Lumpy Investment: Statistics

Notes: The table reports several moments related to the frequency of investment spikes (investment rate above 0.49 in absolute value) and their timing in the data and the model. Specifically, we compare the unconditional frequency of lumpy adjustments, average capital age (years since last lumpy adjustment), and years between two consecutive adjustments. We consider both the sample of firms that do not appear continuously in the survey (Gaps) and firms that appear for at least 10 consecutive years (No Gaps).

data. We find that our model is broadly consistent with the empirical evidence on this untargeted dimension as well.

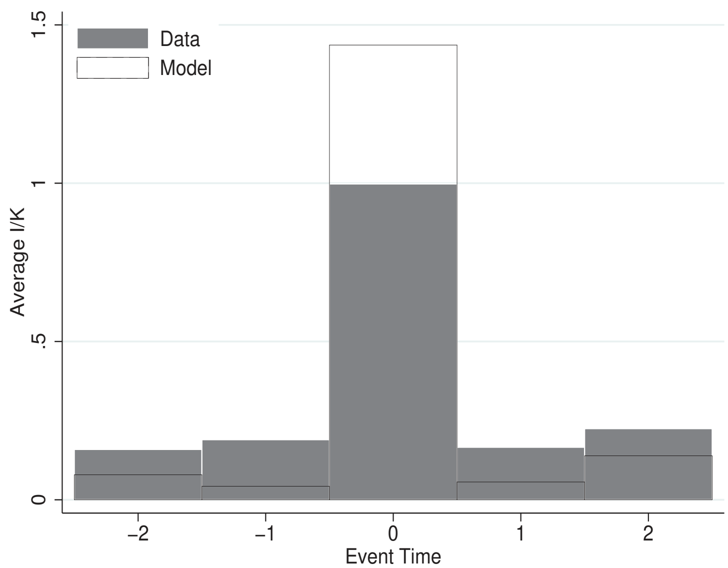


Figure D1: Lumpy Investment: Event Study.

Notes: The figure displays an event study associated with a capital adjustment at time 0 in the data (grey) and the model (white). The bars for time 0 report the average (across all firms) maximum investment rate. The other bars report the average adjustment in the two years preceding and the two years following the maximum adjustment.

Mobility of MRPK. In Table D6 we show that the frictionless model predicts no persistence of MRPK, nor, clearly asymmetry in persistence.

		Tercile at $t+1$		
		1	2	3
Tercile at t	1	0.33	0.33	0.33
	2	0.33	0.33	0.33
	3	0.33	0.33	0.33

Table D6: Mobility (Transition Probabilities) of MRPK in the Frictionless Model.

Notes: The table reports the transition probabilities for terciles of the MRPK distribution in the frictionless model.

D.3 Solution Method for Transitional Dynamics

We now describe how we solve for the transitional dynamics. First, we compute the initial and final stationary equilibrium, using standard methods. We assume that the trade shock unexpectedly hits the economy in its initial stationary equilibrium, at $t = 1$, and that the new stationary equilibrium is then reached by $T = 40$ (we verify that we obtain convergence in a shorter horizon).

We then need to compute a sequence of aggregate price levels $\{P_t\}_{t=1}^{T-1}$ as well as sequences of firm value functions and decision rules (household choices are easily pinned down given the price level). To do so, we iterate between the following two steps until convergence:

- For a given guess for $\{P_t\}_{t=1}^{T-1}$, we solve for firms value function by iterating backward on the Bellman equations, starting from $t = T - 1$ and until $t = 1$.

- Given the decision rules obtained, we use the method developed by Tan (2020) to iterate forward on the transition equation for the distribution of firms over individual states $\lambda_t(k, s)$, starting from $t = 1$ and until $t = T - 1$. In so doing, we compute excess demand in the goods markets and update the aggregate price level accordingly, thus obtaining a new guess for the price sequence.

More details on this algorithm can be found in Ríos-Rull (1998).

D.4 Additional Quantitative Results: Baseline Model

We now provide several additional results related to the effects of the trade shock in the baseline model. Table D7 compares several aggregate variables in the initial and final stationary equilibrium. Figure D2 displays the path of import penetration over time. Figure D3 displays the path of labor employed in manufacturing, comparing baseline model (solid line) and frictionless model (dashed line). Figure D4 displays the path of average productivity among active firms in the baseline model (solid line) and in the frictionless model (dashed line). Table D8 reports the welfare gains from trade, expressed as percentages of permanent consumption, in the baseline and frictionless model, both comparing initial and final stationary equilibrium and accounting for the transition.

VARIABLE	Δ%
C	0.78
K	-10.73
N	-9.92
M	-9.32
TFP^{Adj}	0.92
TFP	-2.32

Table D7: Steady-state Comparison: Before and After Trade Shock.

Notes: The table reports the percentage changes between final and initial stationary equilibrium in aggregate consumption, capital stock, labor in manufacturing, mass of active manufacturing firms, and TFP (both adjusted for the change in the mass of firms and not adjusted).

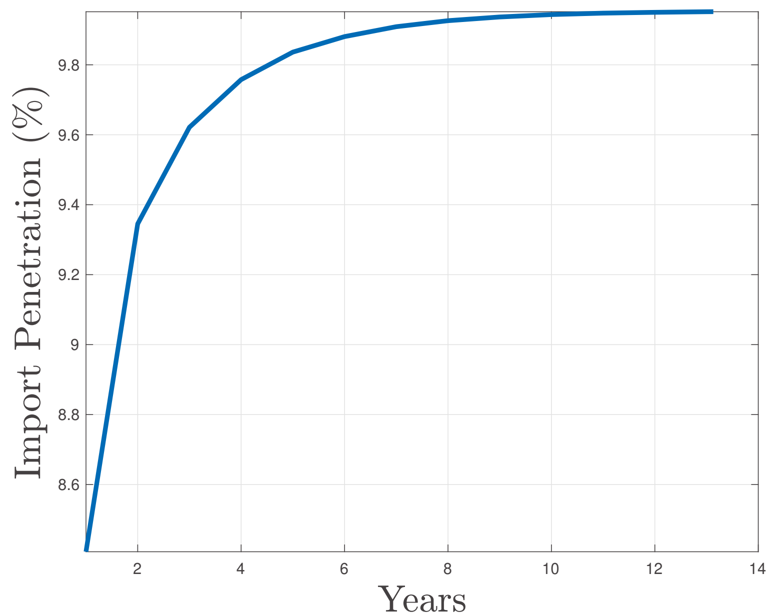


Figure D2: Import Penetration After the Trade Shock.

Notes: The figure displays the path of import penetration, as a percentage of expenditures on consumption goods.

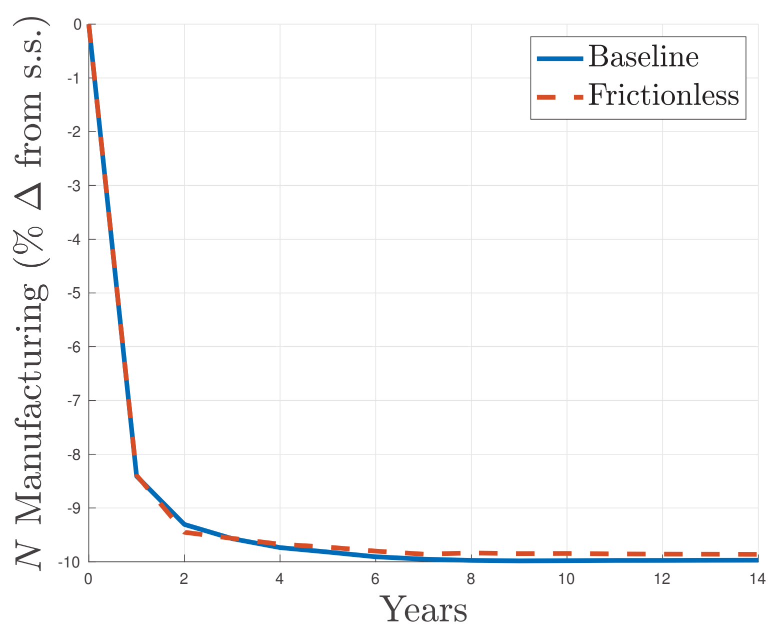


Figure D3: Manufacturing Labor After the Trade Shock.

Notes: The figure displays the transitional dynamics of labor in employed in manufacturing in the baseline model (solid blue line) and in the frictionless model (dashed red). The trade shock hits the economy in period 1. The y-axis reports percentage changes relative to the initial stationary equilibrium.

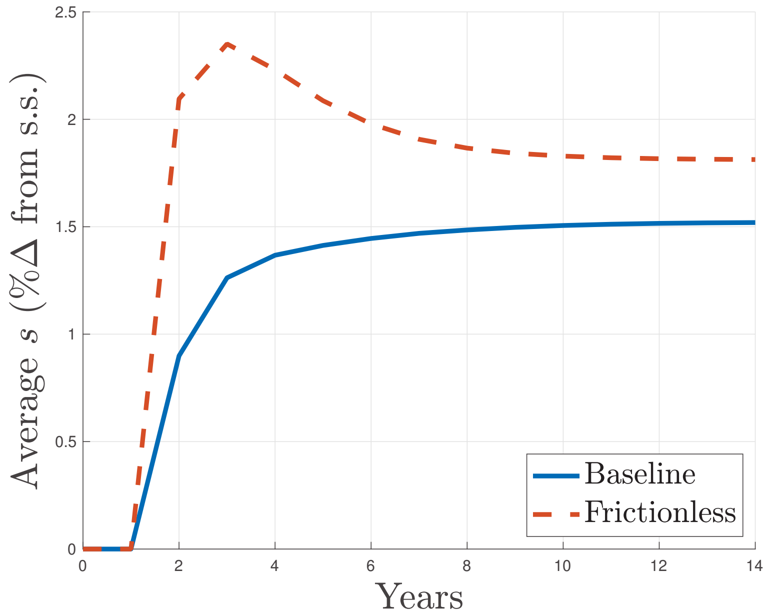


Figure D4: Average Firm Productivity After the Trade Shock.

Notes: The figure displays the transitional dynamics of average firm productivity s in the baseline model (solid blue line) and in the frictionless model (dashed red). The trade shock hits the economy in period 1. The y-axis reports percentage changes relative to the initial stationary equilibrium.

Model	Steady-state	Transition
Baseline	-0.51%	0.19%
Frictionless	-0.69%	0.35%

Table D8: Welfare (Consumption Equivalent Variation).

Notes: The table reports consumption-equivalent welfare gains comparing the final and initial stationary equilibrium (first column) and accounting for the transition (second column).

D.5 Role of General-Equilibrium Forces

We now complement the counterfactual analysis with constant interest rate (Section 8.1). Figure D5 displays the path of aggregate productivity (adjusted for changes in the mass of active firms) TFP_t^{Adj} in the baseline model (solid line) and in the model with constant interest rate (dashed line). A constant interest rate induces largers swings in aggregate productivity, consistent with the findings displayed in Figure 6 and the discussion in Section 8.1.

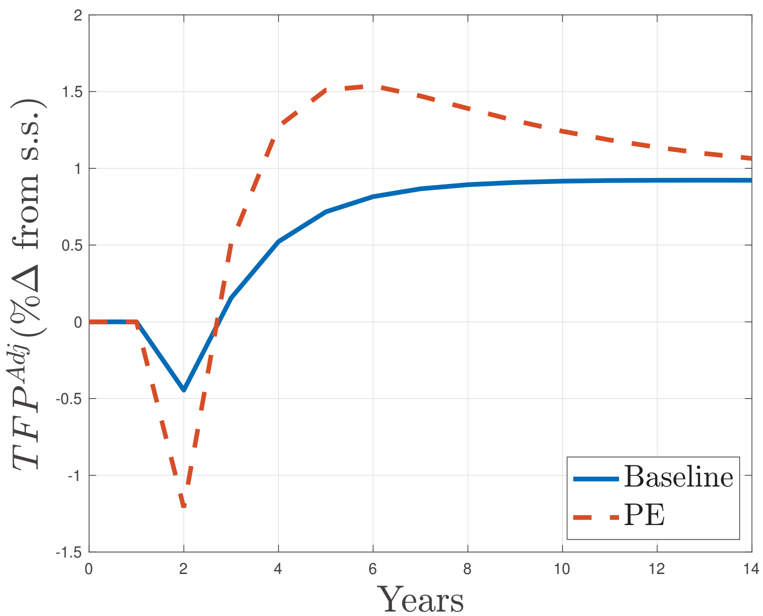


Figure D5: Constant Interest Rate: Aggregate TFP.

Notes: The figure displays the path of aggregate TFP, corrected for changes in the mass of active firms (TFP_t^{Adj}, equation (20)), in the baseline model (solid line) and in the model with constant interest rate (dashed line).

D.6 Convex Adjustment Cost

We now consider the model with partial irreversibility, but no convex cost (Section 8.2). Table D9 reports the calibrated parameter values. This model induces a standard deviation of investment rate that is approximately twice as large as in the data. The other moments are not significantly affected.

Figure D6 displays the path of aggregate productivity TFP_t^{Adj} in response to the trade shock in the baseline model (solid line) and the model without convex cost (dashed line). Figure D7 confirms that the mechanism for productivity dynamics due to shifts in investment and exit thresholds is consistent with our results for the baseline model.

Parameter	Value	Target / Source
ρ	0.783	Autocorrelation of ω
σ	0.797	Standard deviation of ω
q/Q	0.567	frequency of negative investment
ζ	0.186	Slope of exit thresholds
η_0	0.074	Exit rate
η_1	4.861	Relative size at exit
η_2	4.8635	Relative productivity at exit

Table D9: Parameter Values: No Convex Cost.

Notes: The table reports the parameter values for the model without convex cost (Section 8.2).

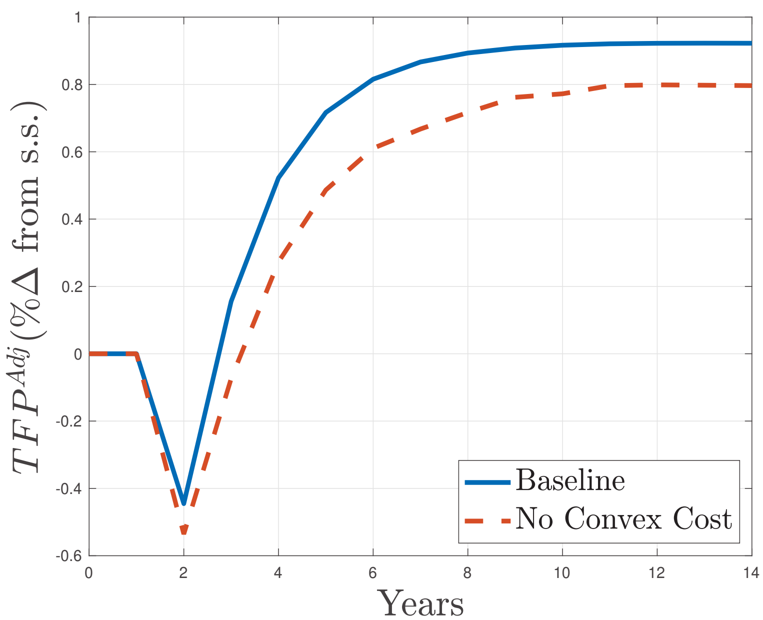
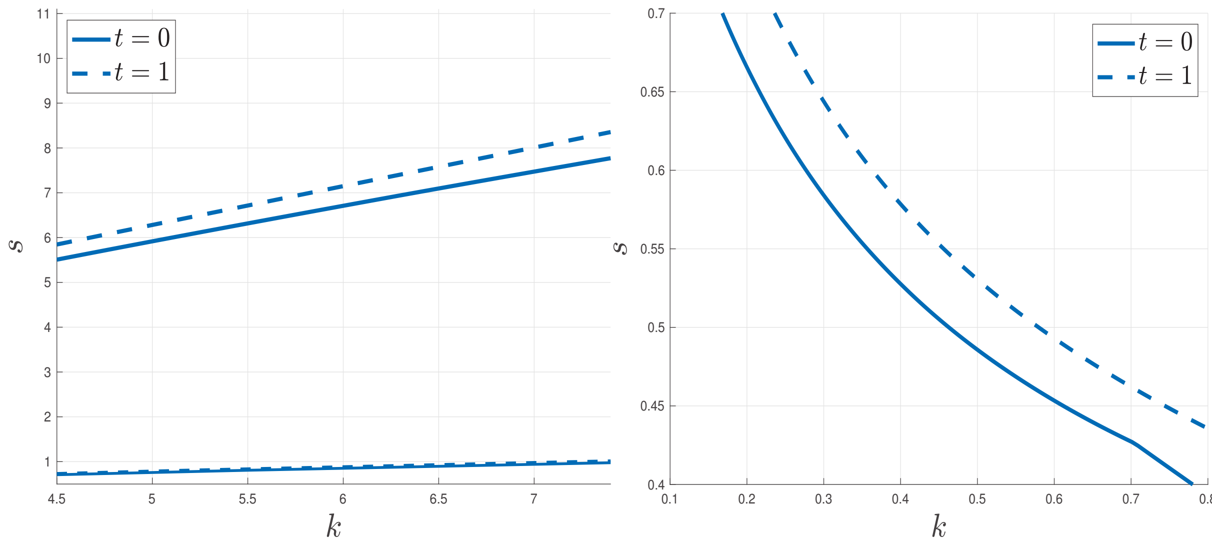


Figure D6: No Convex Cost: Aggregate TFP.

Notes: The figure displays the path of aggregate TFP, corrected for changes in the mass of active firms (TFP_t^{Adj}, equation (20)), in the baseline model (solid line) and in the model without convex cost (dashed line).

D.7 Restriction on the Distribution of Continuation Cost

Our baseline parameterization assumes that the distribution of the fixed continuation cost f depends on the level of firm productivity s. We now investigate a version of the model



(a) Thresholds for Investment and Disinvestment (b) Thresholds for Exit

Figure D7: Role of Convex Cost.

Notes: The left panel displays the thresholds for investment and disinvestment in the model without convex cost, before (solid lines) and immediately after the trade shock (dashed lines). The right panel displays the threshold for exit in the model without convex cost, before (solid lines) and immediately after the shock (dashed lines).

in which the distribution of f is independent of s (Section 8.3). Specifically, we set $\eta_1 = \eta_2 = 0$, which makes the continuation cost independent of firm productivity. We recalibrate this model to target the same moments from the data. Table D10 reports the calibrated parameter values.

In Figure D8 we display the path of aggregate TFP, corrected for changes in the mass of active firms (TFP_t^{Adj}, equation (20)) in the baseline model (solid line), in the model with $\eta_1 = \eta_2 = 0$ and calibrated frictions, and in the frictionless model with $\eta_1 = \eta_2 = 0$. Notice that although aggregate TFP displays a moderate increase on impact in the counterfactual model with frictions, this increase is matched by an even larger increase in the frictionless counterfactual model with $\eta_1 = \eta_2 = 0$. As a result, the short-run aggregate productivity loss relative to a frictionless counterpart is similar in our baseline model and in the model with $\eta_1 = \eta_2 = 0$.

PARAMETER	VALUE	TARGET / SOURCE
ρ	0.739	AUTOCORRELATION OF ω
σ	0.775	STANDARD DEVIATION OF ω
q/Q	0.472	FREQUENCY OF NEGATIVE INVESTMENT
ζ	0.399	SLOPE OF EXIT THRESHOLDS
γ_0	0.003	STANDARD DEVIATION OF i/k
η_0	0.102	EXIT RATE

Table D10: Parameter Values: $\eta_1 = \eta_2 = 0$.

Notes: The table reports the parameter values for the model with $\eta_1 = \eta_2 = 0$.

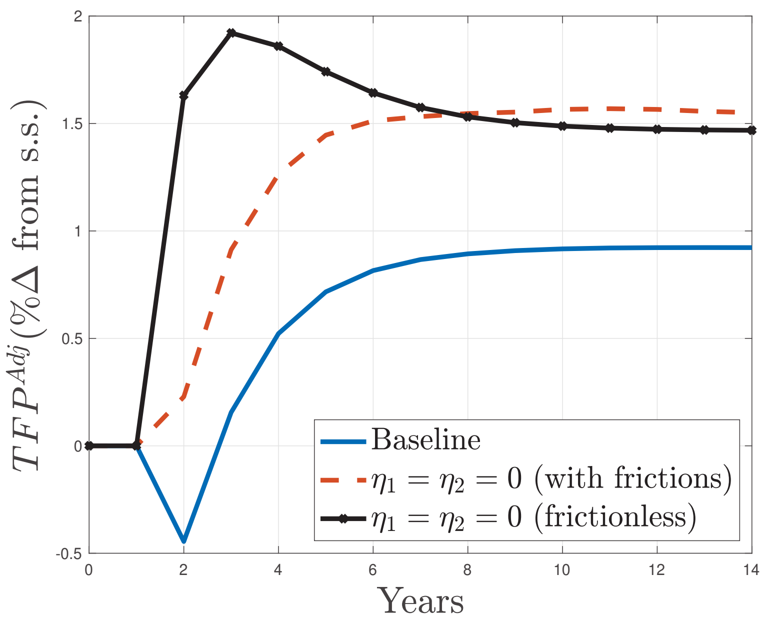


Figure D8: $\eta_1 = \eta_2 = 0$: Aggregate TFP.

Notes: The figure displays the path of aggregate TFP, corrected for changes in the mass of active firms (TFP_t^{Adj}, equation (20)), in the baseline model (solid line), in the model with $\eta_1 = \eta_2 = 0$ and calibrated frictions (dashed line), and in the frictionless model with $\eta_1 = \eta_2 = 0$ (solid line with crosses).

D.8 Higher Dispersion of ω

Because our baseline calibration slightly underpredicts the high dispersion of revenue productivity in the data (Table D1), we perform an additional robustness check, by increasing the standard deviation of productivity shocks to exactly match the dispersion of revenue productivity—at the cost of worsening the fit of some other moments, in particular the dispersion of investment rates increases from approximately 0.8 to approximately 1. To do so, we set $\sigma = 0.865$.

In Figure D9 we display the path of aggregate TFP, corrected for changes in the mass of active firms (TFP_t^{Adj}, equation (20)) in the baseline model (solid line) and in the high-dispersion economy (dashed line), showing that our main results are robust to this modification.

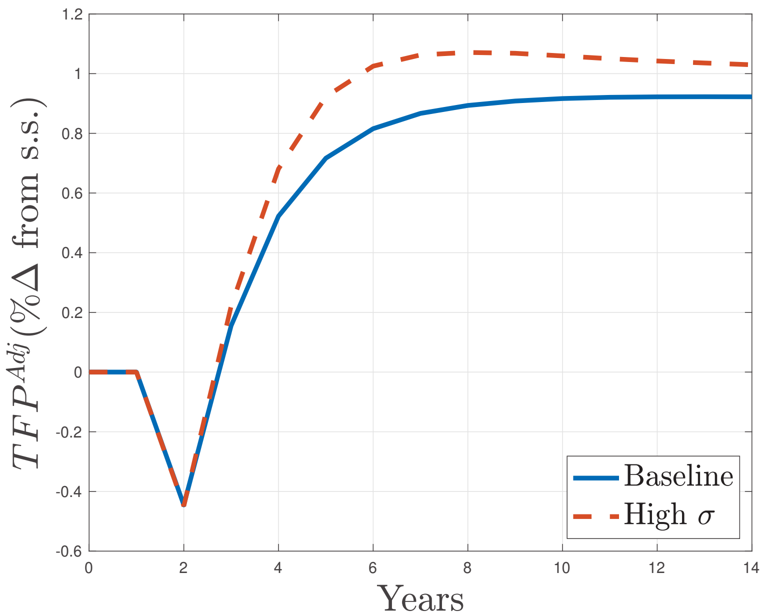


Figure D9: High σ: Aggregate TFP.

Notes: The figure displays the path of aggregate TFP, corrected for changes in the mass of active firms (TFP_t^{Adj}, equation (20)), in the baseline model (solid line) and in the model with high dispersion (dashed line).

D.9 Extension with Multiple Industries

Our baseline model features a single manufacturing industry. We now describe an extension of our model to multiple industries, each populated by heterogeneous firms; we use this framework to validate the mechanism empirically in Section 7.

The economy features a unit-mass continuum of industries $n \in [0, 1]$. Each industry features a continuum of firms, exactly as the single industry in our baseline model.

Households and Final Consumption Good. As in our baseline model, the representative household has utility function (1). The final consumption good that enters this utility function is a Leontief aggregator of the output goods of all industries:

$$C_t = \min_n C_{nt}. \tag{D7}$$

In turn, industry-level output C_{nt} is determined by a CES aggregator of the M_{nt} varieties produced by all (domestic and foreign) firms in industry n, as in our baseline model.

The household budget constraint is

$$\int_0^1 \int_0^{M_{nt}^F} p_{jnt} c_{jnt} dj dn = N_t + \Pi_t, \tag{D8}$$

where the double integral on the left-hand side integrates expenditures over industries and firms within industries.

Because of our assumption of Leontief preferences over industry-level output goods, the optimal allocation of expenditures is such that $C_t = C_{nt}$ for all n. Furthermore, the aggregate price level is $P_t = \int_0^1 P_{nt} dn$, where P_{nt} is the CES price index of varieties produced by industry n. Given this aggregate price level, labor supply satisfies the following optimality condition, as in our baseline model: $\chi C_t = \frac{1}{P_t}$.

Manufacturing Firms. The technology to produce individual varieties, as well as all assumptions related to labor market and investment frictions, are as in our baseline model.

Firm j in industry n at time t faces a demand curve given by

$$p_{jnt} = y_{jnt}^{-\frac{1}{\epsilon}} C_t^{\frac{1}{\epsilon}} P_{nt}, \tag{D9}$$

where ϵ denotes the elasticity of substitution between varieties within each industry.

Accordingly, sales net of labor cost are

$$\pi_{jnt} = P_{nt} C_t^{\frac{1}{\epsilon}} s_{jnt}^{\theta} k_{jnt}^{\theta\alpha} n_{jnt}^{\theta(1-\alpha)} - n_{jnt}. \tag{D10}$$

Firms solve the dynamic program characterized by the functional equations described in Section 3.2, with the only difference that the price index $P(Z)$ denotes the industry-level price index P_{nt}.

The industry-level price index P_{nt} solves the market-clearing condition

$$C_t = \left(\int_0^{M_{nt}^D} y_{jnt}^{\theta} dj + M_{nt}^F \int (c_{nt}^F)^{\theta} dj \right)^{\frac{1}{\theta}}, \tag{D11}$$

where c_{nt}^F are imported goods with measure M_{nt}^F.

Commodity Sector and Balanced Trade. As in the baseline model, the perfectly-competitive commodity sector produces export goods using a linear technology in labor. Commodity exports equal the value of imported varieties of all consumption goods, as well as capital.

Heterogeneous Trade Shocks and Aggregate Dynamics. In constructing industry-specific import-penetration shocks we target two objectives. First, we seek to obtain heterogeneity in industry-level prices P_{nt}, thus generating variation in the investment responses of firms across different industries, consistent with the variation we exploit in the data in Section 7. Second, we seek to ensure that the general-equilibrium dynamics of the aggregate economy are identical to the dynamics of our baseline single-industry economy. Intuitively, we construct shocks such that industry-level import penetration displays some variation around the aggregate path of import penetration of our baseline economy.

With this approach, we can use the empirical evidence of Section 7 to validate the mechanism of our model. It is important to notice that the results described in Section 6 fully account for general-equilibrium effects of the aggregate trade shock. For this reason, it would not be possible to directly compare the response of investment to the aggregate trade shock in our baseline model with the empirical estimates of Section 7. In contrast, our empirical strategy based on cross-industry variation, both in the data and in this multi-industry model, captures heterogeneity in investment dynamics across industries that face common factor-price dynamics, allowing for a meaningful comparison of model and data.

We assume that import competition is heterogeneous across industries because of heterogeneous mass of imported varieties M^F_{nt}.[44] Denote by $\{P^*_t\}^{\infty}_{t=0}$ the aggregate price level sequence that we obtain in our baseline general-equilibrium transitional dynamics in Section 6. To achieve the two targets described above, we feed in the multi-industry model heterogeneous sequences of foreign varieties M^F_n inducing industry-level price indices that satisfy the following restrictions:

$$P_{n1} = P^*_1 z_n, \tag{D12}$$

$$P_{n2} = P^*_2 \frac{P_{n1}}{P^*_1} \tag{D13}$$

$$P_{nt} = P^*_t, \quad t \geq 3 \tag{D14}$$

$$\int_0^1 z_n dn = 1, \tag{D15}$$

[44]Prices of foreign goods are instead constant across industries. This does not affect firm decisions, because the paths of the industry-level price level and aggregate consumption are sufficient statistics for firm choices.

where z_n denotes the impact of the trade shock on the price level of industry n. Industries that are subject to large import-penetration shock (high mass of foreign varieties M_{nt}^F) are associated with values of z_n below its mean. Conversely, industries with limited import-penetration are associated with high values of z_n.

Recall that the aggregate import-penetration shock surprises agents at $t = 1$; after that, the path of available foreign varieties and their price is known and agents have perfect foresight about aggregate variables. To maintain the same set of assumption about firm expectations, we assume that the industry-specific shocks are such that their effects on prices arise and surprise agents at $t = 1$, persist at $t = 2$, thus affecting investment decisions, and then revert to the aggregate path at $t = 3$.

To obtain the estimates of interest in the model, we leverage cross-industry variation in import penetration $\frac{\int_{M_{nt}^D}^{M_{nt}} p_{nt}^F c_{nt}^F dj}{P_{nt} C_t}$ at $t = 1$ (when agents are surprised) and outcome variables at $t = 1, 2$. In particular, we consider a simulated sample of 32 different industries. We feed industry-level shocks in import penetration that induce a standard deviation of prices P_{n1} of approximately 1%. We verify that the relationships we estimate are approximately linear and thus do not depend significantly on the size of these shocks.

E Empirical Effects of Trade Shocks

In this appendix, we provide additional details and results on the empirical effects of trade shocks on capital reallocation.

E.1 Export Dynamics

A potential effect of China's WTO accession on the Peruvian manufacturing industry is the increase in market access for exports. To illustrate that this effect was quite limited for manufacturing, Figure E1 shows the share of Peruvian exports to China relative to total Peruvian exports at the 2-digit industry level during the period 2000-2013. China represented a large export market, but only to some industries. The industries that substantially expanded their exports to China are mostly in the commodity sector. In particular, these are forestry, fishing, metal ores. This is not the case for the manufacturing industries of interest for our analysis. Most of these industries did not see any increase in exports to China.

These facts inform our modeling choices in Section 3: in particular, the assumption that the manufacturing sector does not export, while commodity producing firms export their output.

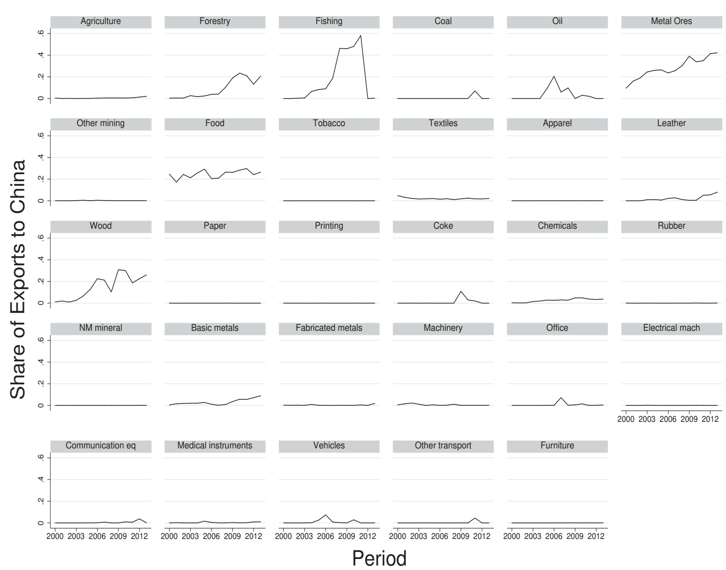


Figure E1: Export Intensity to China.

Notes: The figure displays export shares of Peruvian manufacturing industries to China at the 2-digit CIIU levels during the period 2000 to 2013.

E.2 Import-Competition Shock

In Table E1, we summarize the two main measures of the trade shock, previously described in Section 4.2. $ImpInt_{nt}$ is the share on total imports of goods originated in China, by 4-digit CIIU Rev 3 industry codes. $ChComp_{nt}$ is our preferred measure and refers to the deviation from import intensity trends by 2-digit industry.

	Mean	Std.Dev.	Min	Max
ChComp$_{nt}$	0.00	0.12	-0.59	0.39
ImpInt$_{nt}$	0.21	0.23	0.00	0.80

Table E1: Import-Competition Shock.

Notes: The table reports the main summary statistics for the two measures of import competition shocks defined in Section 4.2. For both measures, we include the mean, standard deviation, minimum and maximum value.

Moreover, in Table E2, we provide the first-stage regression of our baseline instrumental analysis. To instrument for $ChComp_{nt}$, we include information from countries that share a geographical border with Peru.

	$ChComp_{nt}$
$ChCompCHI_{nt}$	0.565
	(0.010)
$ChCompCOL_{nt}$	-0.060
	(0.016)
$ChCompECU_{nt}$	-0.315
	(0.011)
$ChCompBOL_{nt}$	0.098
	(0.010)
$ChCompBRA_{nt}$	0.257
	(0.012)
F-stat	711.00

Table E2: Import-Competition Shock Instrument - First Stage.

Notes: The table reports the first stage regression for our instrumental variable analysis. The countries included to instrument for $ChComp_{nt}$ are Chile, Colombia, Ecuador, Bolivia, and Brazil. F-stat for our first stage is reported. The number of observations is 11,560.

E.3 Effects of Trade Shocks on MRPK Dispersion: Robustness

We provide several additional results related to the effects of the trade shock on MRPK dispersion. First, we verify that the trade shock only produces a transitory effect by estimating the following lagged pass-through regression

$$\Delta\sigma_{nt}^{MRPK} = \alpha_0 + \alpha_1 \Delta ChComp_{n,t-1} + \alpha_2 \Delta ChComp_{n,t-2} + \gamma_m + \epsilon_{nt} \tag{E1}$$

where $\Delta y_t = y_t - y_{t-1}$. Figure E2 shows the cumulative efects for one and two years after the import competition shock, i.e., α_1 and $\alpha_1 + \alpha_2$. As shown, the effect is only statistically and economically significant for one year, after which it fades out.

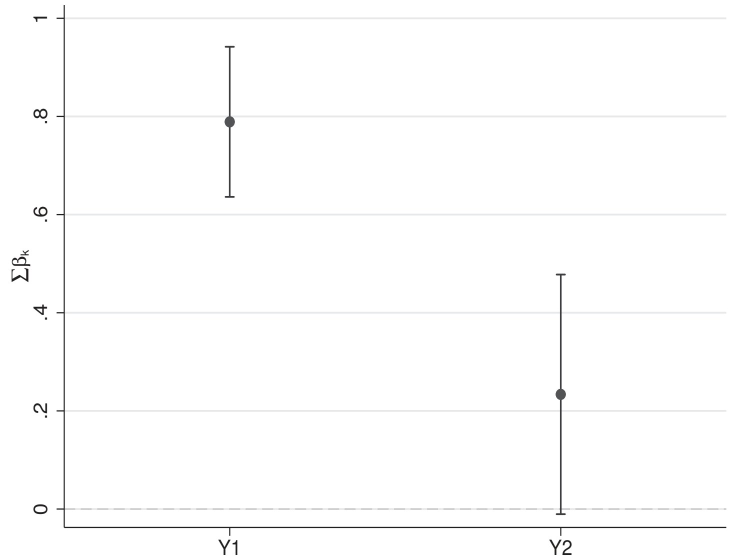


Figure E2: The Transitory Effect of a Trade Shock on MRPK Dispersion.

Notes: The figure displays the cumulative effect of the trade shock on the dispersion of MRPK. The coefficient α_1 refers to the effect one year after the shock (Y1), whereas for year 2 (Y2), the figure displays the cumulative effect $\alpha_1 + \alpha_2$. Intervals at the 99% confidence level are also included and robust standard errors are considered.

Then, we confirm that the predictions of Panel (a) of Table 3 are robust to considering MRPK dispersion at the 2-digit level, for which we calculated several moments in the data for our calibration exercise. Table E3 shows the results, which are not statistically different to the ones of Table 3.

	σ_{mt}^{MRPK}	
	Full Sample	Large firms' Sample
$ChComp_{nt-1}$	0.135	0.088
	(0.017)	(0.022)

Table E3: The Effect of a Trade Shock on MRPK Dispersion.

Notes: The table reports our estimates for δ_1 in equation (21). Robust standard errors are in parentheses. In the full sample specification (first column), σ_{MRPK} is calculated at the 2-digit industry-year level considering all firms. It encompasses 427 4-digit industry-year observations. In the large firms' sample (second column), σ_{MRPK} is calculated at the 2-digit industry-year level considering only firms with annual net sales above 2 million soles, for which the survey is a census. This sample has 410 4-digit industry-year observations.

Third, we check that these results hold for the sample pre-2003, only a year after China's WTO accession. For this sample, the identifying variation in the data comes only from differences across industries, similar to our estimates in the model. Table E4 reports the coefficients. While these estimations are associated with less statistical power, they report similar estimates to the ones of Panel (a) in Table 3 and in line with the model counterpart.

	σ_{nt}^{MRPK}	
	Full Sample	Large firms' Sample
$ChComp_{nt-1}$	0.194	0.399
	(0.096)	(0.105)

Table E4: The Effect of a Trade Shock on MRPK Dispersion before 2003.

Notes: The table reports our estimates for δ_1 in equation (21) for the sample pre-2003. Robust standard errors are in parentheses. In the full sample specification (first column), σ_{MRPK} is calculated at the 4-digit industry-year level considering all firms. It encompasses 95 4-digit industry-year observations. In the large firms' sample (second column), σ_{MRPK} is calculated at the 4-digit industry-year level considering only firms with annual net sales above 2 million soles, for which the survey is a census. This sample has 87 4-digit industry-year observations.

Finally, in Table E5, we provide several robustness analyses to our baseline specification of equation (21), such as considering alternative measures of import competition and additional sets of instruments. Moreover, we also provide the OLS estimates for our baseline specification. The first column uses as import-competition shock the level of Chinese import penetration by industry, $ImpInt_{nt}$. In addition, the second column reports the results using the additional set of instruments—imports originated in China to other upper-middle-income countries such as Mexico, Costa Rica, and South Korea, instead of imports from China to Peru. Finally, the third columns reports the OLS estimates for our baseline specification. In all cases, our baseline estimates are confirmed by these robustness checks.

	σ_{nt}^{MRPK}		
	Alternative Measure	Alternative Instrument	Baseline OLS
$ChComp_{nt-1}$		0.242	0.044
		(0.049)	(0.025)
$ImpInt_{nt-1}$	0.310		
	(0.030)		

Table E5: The Effect of a Trade Shock on MRPK Dispersion.

Notes: The table reports our estimates for δ_1 in equation (21) for the full sample. Robust standard errors are in parentheses. The first column reports the empirical estimates when considering the level of Chinese import penetration by industry, $ImpInt_{nt}$ (the number of observations is 398 4-digit industry-year observations); the second column refers to our baseline trade shock measure instrumented by the imports of other upper-middle-income countries such as Mexico, Costa Rica, and South Korea (the number of observations is 396 4-digit industry-year observations); the third column shows the OLS specification of our baseline estimates (the number of observations is 400 4-digit industry-year observations).

E.4 Effects of Trade Shocks on Selection: Robustness

We illustrate the outward shift in the survival isoprobability lines in Figure E3 associated with a one-standard-deviation trade shock on survival probability following equation (23).

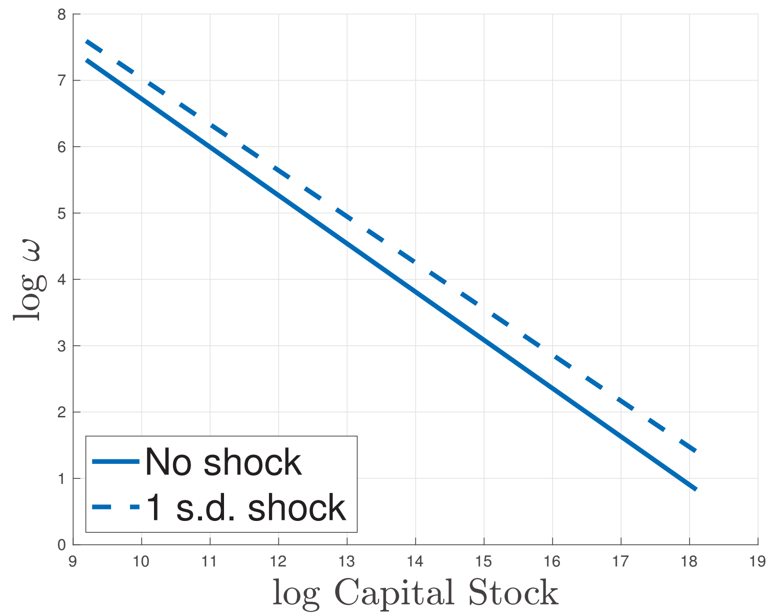


Figure E3: Effects of Trade Shock on Survival Probabilities.

Notes: The figure displays the effect of a 1-standard-deviation trade shock on survival probability. The solid line represents the isoprobability line (50% survival probability) without trade shocks. The dashed line refers to the same isoprobability line when firms face a 1-standard-deviation trade shock. The import-competition measure is $ChComp_{nt}$ and is instrumented using imports from China to border Latin American countries.

E.5 Input-Output Matrix and Other Robustness Checks

We perform several robustness checks of the empirical analysis of Sections 7.2, 7.3 and 7.4.

Intermediate Goods. We consider the effect of a trade shock on the use of intermediate goods by a firm. Another potential channel through which China's WTO accession could benefit domestic firms is the access to cheaper intermediate goods. In the case of intermediate goods, China import shares increase over the years, but the increase in importance is not immediate. In 2002, China is 7th on the ranking, with only 4.4% of import shares. By 2005, this percentage increases to 7.0% and China rises as the sixth leading source country. However, it is only by 2011 that China becomes the leading source country of Peru in this product group. While important, in the short-run, the impact of the increase in imported inputs is relatively muted compared to the fast increase in imports of final goods.

Nevertheless, a more nuanced concern, in this case, is that within industries, it might be large firms that are more able to benefit from access to imported intermediates, and this could, in turn, explain why these firms are not downsizing their capital stock or exiting. To address this concern, we explicitly control for firms' potential access to cheaper intermediate goods due to China's accession to the WTO. In particular, we construct an industry measure of access to Chinese intermediate goods that considers how each industry relies on intermediate goods from other sectors, as follows,

$$IOshock_{kt} = \sum_{h} sh^{IO}_{hk} ImpInt_{ht}. \tag{E2}$$

In this equation, $IOshock_{kt}$ represents, for each manufacturing industry k, a weighted-average measure of import penetration in industries h that industry k uses as inputs, where the weights sh^{IO}_{hk} are based on the direct requirements coefficients of h's use in the production of k from the Peruvian input-output table from the Economic Census of 2007. This data, however, is not disaggregated at the same level of 4-digit CIIU but rather according to a national classification used in the national accounts. Therefore, we use concordance tables from the Peruvian government to assign 4-digit CIIU industries to this broader classification.

Armed with this additional data, we verify that imported intermediate inputs are not biasing our results regarding these two margins—growth of capital and firms' survival—by estimating the effects of import competition, controlling for the variable $IOshock_{kt}$.

For the growth rate of capital, we use the following specification,

$$z_{jnt} = \beta_0 + \beta_1 ChComp_{nt} + \beta_2 \log(\omega_{jnt}) + \beta_3 \log(k_{jnt}) + \gamma_n + \gamma_t + \epsilon_{jnt} \tag{E3}$$

where z_{jnt} is the log of the growth rate of capital. Moreover, we include 4-digit industry fixed effects γ_n as well as year fixed effects γ_t. For the survival regression, we use the specification presented in equation (23).

We show the results in Tables E6 and E7. Table E6 refers to the impact of our main variables on the growth rate of capital of firms, while Table E7 considers firms' survival (selection). In all the specifications, the effects of import competition are robust to the inclusion of this variable. For example, the first and second columns of Table E6 compare the results on the growth rate of capital, with and without controlling for the gained access to cheaper intermediate inputs. The coefficients in all variables of these two specifications are statistically indistinguishable. Moreover, the coefficient associated with $IOshock_{kt}$ is not statistically significant. The same patterns hold when considering a fully interacted version of our baseline specification (third and fourth column). We obtain a similar result for the probability of survival, with the results displayed in Table E7. Overall, given these findings, we conclude that, in our sample period, intermediate input access likely did not affect the main empirical patterns of reallocation.

	Log Growth Rate k_{jt}			
$\log(\omega_{jnt})$	0.128	0.128	0.129	0.129
	(0.024)	(0.024)	(0.024)	(0.024)
$\log(k_{jnt})$	-0.095	-0.095	-0.094	-0.094
	(0.011)	(0.011)	(0.010)	(0.011)
$ChComp_{nt}$	-0.052	-0.088	-2.497	-2.564
	(0.217)	(0.229)	(1.466)	(1.502)
$\log(k_{jnt}) * ChComp_{nt}$			-0.137	-0.136
			(0.090)	(0.089)
$\log(\omega_{jnt}) * ChComp_{nt}$			0.526	0.527
			(0.243)	(0.244)
IOshock_{kt}		0.056		0.055
		(0.124)		(0.125)

Table E6: The Effect of a Trade Shock on Capital Growth.

Notes: The table reports our estimates from our firm-level regressions that consider the effect of a trade shock on the log of the growth rate of capital (equation (E3)). Clustered standard errors at the firm-level are in parentheses.

	Probability of Survival			
$\log(\omega_{jnt})$	0.280	0.281	0.280	0.281
	(0.018)	(0.018)	(0.018)	(0.018)
$\log(k_{jnt})$	0.203	0.203	0.202	0.203
	(0.009)	(0.009)	(0.009)	(0.009)
$ChComp_{nt}$	-0.825	-0.665	-4.052	-3.832
	(0.507)	(0.552)	(1.986)	(2.025)
$\log(k_{jnt}) * ChComp_{nt}$			0.158	0.154
			(0.085)	(0.086)
$\log(\omega_{jnt}) * ChComp_{nt}$			0.134	0.127
			(0.209)	(0.209)
IOshock_{kt}		-0.203		-0.142
		(0.288)		(0.289)

Table E7: The Effect of a Trade Shock on Survival.

Notes: The table reports our estimates from our firm-level regressions that consider the effect of a trade shock on the probability of survival. Clustered standard errors at the firm-level are in parentheses. We follow our specification in equation (23).

Other Robustness Checks. We now provide several robustness analyses for equation (22) and (23), such as considering alternative measures of import competition and additional sets of instruments. Moreover, we also provide the OLS estimates for our baseline specification. First, Table E8 shows the additional results for equation (22). The first column uses as import-competition shock the level of Chinese import penetration by industry, $ImpInt_{nt}$. In addition, the second column reports the results using the additional set of instruments—imports originated in China to other upper-middle-income countries such as Mexico, Costa Rica, and South Korea, instead of imports from China to Peru. Finally, the third column reports the OLS estimates for our baseline specification. In all cases, our baseline estimates are confirmed by these robustness checks.

	Alternative Measure	Alternative Instruments	Baseline OLS
	$ImpInt_{nt}$	$ChComp_{nt}$	$ChComp_{nt}$
Inaction	0.304 (0.057)	0.432 (0.091)	0.230 (0.057)
Positive Investment	-0.544 (0.065)	-0.468 (0.105)	-0.268 (0.064)
Negative Investment	0.240 (0.036)	0.036 (0.058)	0.038 (0.037)

Table E8: Effect of Trade Shock on Investment.

Notes: The table reports our estimates for δ_1 in equation (22). The first row refers to inaction (absolute value of investment rate less than 10%); the second row refers to positive investment (investment rate larger than 10%); the third row refers to negative investment (investment rate less than -10%). The first column reports the empirical estimates when considering the level of Chinese import penetration by industry, $ImpInt_{nt}$ (the number of observations is 6,245); the second column refers to our baseline trade shock measure instrumented by the imports of other upper-middle-income countries such as Mexico, Costa Rica, and South Korea (the number of observations is 6,413); the third column shows the OLS specification of our baseline estimates (the number of observations is 6,417). Standard errors clustered at the firm level in parenthesis.

Second, we provide the estimates for the robustness analysis of equation (23) in Table E9. As before, the first column uses as import-competition shock the level of Chinese import penetration by industry, $ImpInt_{nt}$, while the second column corresponds to the results using the additional set of instruments that consider imports from China to other upper-middle-income countries such as Mexico, Panama, and South Korea. Moreover, the third column considers this specification for the period post-2007, where our measure of exit is corrected with the firm registry for all firms in the survey. Given there is not much variation within a 4-digit industry, we use 2-digit industry fixed effect in this regression to control for permanent differences in survival rates by industry. These coefficients suggest an increase in the probability of exit due to an import competition shock. Importantly, the estimates from the second and third column—which use a comparable shock—imply an increase of the exit rate of 1.3, and 1 percentage points, respectively. Finally, the fourth column reports the OLS specification of our baseline estimates.

	Alternative Measure	Alternative Instrument	Post-2007 Sample	Baseline OLS
$\log(\omega_{jnt})$	0.281	0.281	0.351	0.281
	(0.018)	(0.018)	(0.029)	(0.018)
$\log(\text{k}_{jnt})$	0.204	0.205	0.245	0.206
	(0.009)	(0.008)	(0.012)	(0.008)
$ChComp_{nt}$		-0.549	-0.570	-0.186
		(0.531)	(0.260)	(0.207)
$ImpInt_{nt}$	-0.869			
	(0.349)			

Table E9: Effect of Trade Shock on Survival.

Notes: The table reports our estimates for β_1 in equation (23). The first column uses the alternative measure $ImpInt_{nt}$ as import competition shock (the number of observations is 11,554); the second column refers to our baseline trade shock measure instrumented by the imports of other upper-middle-income countries such as Mexico, Costa Rica, and South Korea (the number of observations is 12,002); the third column includes to our baseline measure of import competition but for the sample period post-2007 (the number of observations is 6,803); the fourth column shows the OLS specification of our baseline estimates (the number of observations is 12,009). In all four specifications, standard errors, clustered at the firm-level, are in parentheses.

In addition to these robustness checks, we also use our firm-level depreciation measure to investigate the role of capital composition. In particular, to understand the effects of firm-level depreciation on inaction and investment dynamics, we estimate the following specification:

$$\begin{aligned} z_{jnt} &= \alpha_0 + \alpha_1 ChComp_{nt} + \beta ChComp_{nt} * I[DepQuantile]_{jnt} + \alpha_3 \log(\omega_{jnt}) \\ &\quad + \alpha_4 \log(k_{jnt}) + \alpha_5 I[DepQuantile]_{jnt} + \gamma_n + \epsilon_{jnt}, \end{aligned} \tag{E4}$$

where $I[DepQuantile]_{jnt}$ refers to dummy variables for quantiles of firm-level depreciation rates. Quantile 1 represents the lowest capital depreciation firms, whereas quantile 4 consists of the highest ones.

We show the results in Table E10. We only include the β coefficients, i.e., the effect of the shock by each quartile of the firm-level depreciation distribution relative to the first one. The first row refers to the impact of the competition shock on the base category. The second row refers to the additional impact, relative to base category, of the second quartile, and so on. The competition shock increases the probability of inaction for firms in the first quartile of the distribution. However, the effect becomes more muted for firms in the upper quartiles. The same pattern exists for the probability of positive (negative) investment, where firms in the first quartiles are more negatively (positively) affected than firms in the upper quartiles. These results show than firms with lower firm-level depreciation rates are the ones responsible for the aggregate effects seen in Panel (b) of Table 3.

	Inaction	Positive Investment	Negative Investment
ChComp_{nt}	0.627	-0.770	0.142
	(0.144)	(0.148)	(0.095)
$\text{ChComp}_{nt} * \delta q2_{jnt}$	-0.266	0.312	-0.046
	(0.153)	(0.153)	(0.100)
$\text{ChComp}_{nt} * \delta q3_{jnt}$	-0.120	0.210	-0.089
	(0.150)	(0.158)	(0.112)
$\text{ChComp}_{nt} * \delta q4_{jnt}$	-0.228	0.363	-0.135
	(0.154)	(0.169)	(0.119)

Table E10: The Effect of a Trade Shock on Investment (continued).

Notes: The table reports our estimates for the β coefficients in equation (E4). The first column refers to inaction (absolute value of investment rate less than 10%); the second column refers to positive investment (investment rate larger than 10%); the third column refers to negative investment (investment rate less than -10%). The number of observations is 6,413. Standard errors clustered at the firm level in parenthesis.