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Welfare Effects of Industrial Policies: Theory and Evidence from India's De-reservation Policy

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Abstract*

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We study how industrial policies affect welfare depending on firms' management practices. In a model of multi-product firms, we show that firms with better management practices are less adversely affected by an industrial policy that fosters market entry and competition. This result follows from firms with better management practices specializing in fewer products with lower marginal costs. Evidence from India's de-reservation policy supports these predictions. Our simulations estimate a 0.29% welfare gain in India from the policy. The same policy could increase welfare by 0.39% in an environment with better management practices, such as those in the US.

Keywords: industrial policies, management practices, multi-product firms, de-reservation policy
JELs: D24, F10, L25, O12, O25

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1 Introduction

Industrial policies are experiencing a surge of interest among economists and governments. Recent empirical evidence shows that industrial policies can promote industrialization, technological change, and productivity. However, the effectiveness of these policies can vary in different settings (Barwick et al., 2025; Lane, 2025). One potential reason for this heterogeneity is the difference in management practices across sectors and countries. Bloom et al. (2010) show that poor management practices are associated with lower levels of firm productivity. Can management practices be the reason for the heterogeneous performance of some industrial policies?

This paper examines the role of management practices in shaping the aggregate welfare effects of industrial policies. We think of management practices as a technology or knowledge that influences the efficiency with which organizational capital (a collection of business processes, systems, and a distinct corporate culture) is used within the firm. To investigate this, we leverage India's de-reservation policy between 2000 and 2008 as an exogenous industrial policy shock. This policy lifted restrictions that previously reserved 11.8% of products for small-scale enterprises (SSE), accounting for 28.3% of the total production in the SSE sector in 1988. Using a novel measurement of firm-level management practices together with the de-reservation policy, we are the first ones to provide evidence on how management practices shape the aggregate welfare effects of industrial policies.

Motivated by novel empirical evidence on the effects of the de-reservation policy in India, we develop a theoretical model that integrates management practices into a model of multi-product firms. Our model allows us to analyze the role of management practices in firms' output and product scope adjustments after the de-reservation policy. We bring the model predictions to the data using India's Annual Survey of Industries (ASI), a firm-level panel data from 2000 to 2008.[1] We exploit the exogenous de-reservation of individual products over time for identification. Next, we estimate the model parameters and simulate the Indian economy to measure the aggregated welfare gains derived from the de-reservation policy. Finally, we estimate what the welfare gain would have been had the industrial policy been implemented in an environment with the average level of management practices of the US.

[1]While the ASI samples establishments, we refer to them as firms throughout the paper.

In our model, firms are heterogeneous in their endowment of organizational capital and management practices. Organizational capital relates to the operating, investment, and innovation capabilities of a firm (Lev and Radhakrishnan, 2005). As in Nocke and Yeaple (2014), we assume that the more organizational capital is used for the production of a given product, the lower is its marginal cost. Management practices govern how effective organizational capital is in decreasing the firm's marginal cost and firms endogenously choose which products to produce and how to allocate their limited supply of organizational capital across products.

The main result of the model is that firms with better management practices are less adversely affected by the de-reservation policy. The specific mechanism behind this result is that, because organizational capital is limited, firms with better management practices specialize in producing fewer products with lower marginal costs. The lifting of restrictions following the de-reservation policy caused an increase in competition in the de-reserved products. By having their sales concentrated in their better-performing products, firms with better management practices experience a smaller decrease in their output and product scope due to the increase in competition. Furthermore, the model predicts that this mechanism is more relevant in sectors with greater product heterogeneity, because it relies on firms being able to specialize in their most productive products.

From the early 1990s, India adopted a broad range of liberalization reforms, including tariff reductions, de-licensing, and FDI liberalization. The de-reservation policy was part of this economy-wide reform package and not a reaction to shocks in any particular sector. The main criteria based on which de-reservation was recommended by the Advisory Board were the necessity of higher R&D investments, safety and hygiene considerations, and better utilization of available resources, among others (Hussain, 1997). These criteria were unrelated to the performance of the firms producing each product, which makes the timing of each product's de-reservation plausibly exogenous. Additionally, we check for pre-trends and find no significant correlation between the lagged growth rate of product-level characteristics and the timing of de-reservation. We link de-reserved products to firms using a firm's main product (the product with the largest output), and exploit the plausibly exogenous timing of the de-reservation policy in India in a difference-in-differences framework to test the model predictions. Furthermore, we differentiate between incumbents, firms that produced a reserved product before its de-reservation, and entrants, firms that started producing a product after it was de-reserved.

Our results show that product de-reservation fostered entry of new firms into the product space, while incumbent firms reduced both their output and product scope after their main product was de-reserved. These negative effects are decreasing in firms' management practices: firms in the third quintile of management practices experienced close to no effect, while firms in the last quintile decreased their output by 33%. Incumbent firms with better-than-average management practices managed to increase their output after their main product was de-reserved. Our empirical results also show support for the model's mechanism, with stronger effects in sectors with larger product heterogeneity. Our results are robust to using the share of de-reserved products at the industry level and a wide range of alternative measures of management practices.

Finally, we assess the importance of management practices on the aggregate welfare effect of an industrial policy. To do so, we estimate the model parameters for each manufacturing sector using the Simulated Method of Moments and the ASI. We then explore different scenarios in which we simulate the de-reservation policy and changes in the average levels of management practices. Our estimations show a 0.29% welfare gain of the de-reservation policy in India. This effect is around the same order of magnitude as the 1% welfare increase found by Choi and Levchenko (2025) for the effects of heavy and chemical industrial policy in South Korea. However, the same policy in an environment with better management practices, such as the US, would lead to a 0.39% welfare gain, a 36% relative increase. This indicates that management practices can play a significant role in the aggregate welfare gains of industrial policies.

This paper contributes to three different strands of literature. First, it is related to the growing literature on industrial policies (see Juhász et al. (2024) for a review). In recent years, there has been growing evidence on the effects of industrial policies on industrialization (Lane, 2025), employment (Martin et al., 2017; Criscuolo et al., 2019), productivity (Rotemberg, 2019), and technological change (Alfaro et al., 2025). We complement this literature by looking at the effects of industrial policies on welfare.[2] Choi and Levchenko (2025) also look at the effects of industrial policies on welfare. However,

[2]We study this industrial policy in the context of India. Several papers have studied the effects of this liberalization period on firm-level outcomes in India (Goldberg et al., 2010a,b; Topalova and Khandelwal, 2011; Nataraj, 2011; Hasan et al., 2012; Ahsan and Mitra, 2014; Asturias et al., 2019; Bau and Matray, 2023). We complement this strand of research by showing how competition increased welfare in the context of the de-reservation policy.

relative to their work, we make three main contributions. First, we document that firms react differently to industrial policies depending on their management practices. This is important because the literature has shown that there is a large heterogeneity in management practices across firms and countries (Bloom and Van Reenen, 2010; Bloom et al., 2010; Caselli and Gennaioli, 2013; McKenzie and Woodruff, 2017). Guner et al. (2018) show that distortions that weaken incentives for managerial earnings substantially reduce managerial quality and output, explaining more than half of the output gap between the US and Italy. More broadly, cross-country differences in distortions account for about 42% of the variation in output per worker relative to the US. These differences in management practices can lead to varying effects of an industrial policy. Second, we explore an increase in competition as the channel through which an industrial policy can affect welfare. This channel has been understudied in the literature, which has focused on spillover effects from targeted to non-targeted firms and industries, and the dynamic effects of learning-by-doing (Goldberg et al., 2024; Lane, 2025; Alfaro et al., 2025). Third, we show that the aggregate welfare effect is different depending on the level of management practices in the country. If the same industrial policy were implemented in an environment with the management practices level as in the US, the aggregate welfare gains would have been 36% larger than our estimated effect for India.

Second, this paper also contributes to the literature quantifying the importance of misallocation for aggregate outcomes (Hsieh and Klenow, 2009; Garcia-Santana and Pijoan-Mas, 2014; Restuccia and Rogerson, 2017; Guner et al., 2018; Bau and Matray, 2023; Wang and Yang, 2023; Uras and Wang, 2024; Xie et al., 2024). Similar to Garcia-Santana and Pijoan-Mas (2014) and Bau and Matray (2023), we leverage a liberalization episode to estimate the effect of an industrial policy on misallocation in the affected industries. Our paper complements these two papers by focusing on measuring aggregate welfare gains rather than TFP. This distinction is important in our case because one of the mechanisms through which the reservation policy affects aggregate welfare is by incentivizing firms with worse management practices to increase their product scope.[3] As the de-reservation policy changes the number of products available to consumers, welfare, rather than TFP, becomes the relevant measure of misallocation. Wang and Yang (2023) show the importance of incorporating the product scope channel when studying

[3] This mechanism has been shown in other contexts: see, for example, Eckel and Neary (2010) and Dhingra (2013).

misallocation, as they estimated 24% of the welfare losses stem from distortions along the product margin.

Finally, this paper is also related to the literature on multi-product firms, particularly to Eckel and Neary (2010), Iacovone and Javorcik (2010), Bernard et al. (2011), Dhingra (2013), Mayer et al. (2014), Nocke and Yeaple (2014), Lopresti (2016), Eckel et al. (2023), and Macedoni et al. (2024). One result of this literature is that multi-product firms adjust their product scope in reaction to demand factors and competition. However, most of this literature has been focused on demand linkages, mainly the cannibalization effect across products, while supply linkages have attracted much less attention. In a recent paper, Eckel et al. (2023) exploit anti-dumping duties as a cost shock and look at the response of non-affected products in affected and non-affected destinations using Chinese firm-level customs data. They document the presence of demand and supply linkages across products produced within a firm and show that multi-product firms react by increasing exports of non-affected products in the country that imposed the duty. This paper complements the others in this literature by including management practices as a source of supply linkages within a firm, and how they can cause a heterogeneous reaction of multi-product firms to increased competition.

The remainder of this paper is structured as follows. Section 2 provides some background on the de-reservation policy. Section 3 introduces the data and shows empirical regularities related to the de-reservation policy. Section 4 introduces the theoretical model. Section 5 develops the empirical strategy used to test the model predictions. Section 6 presents the empirical results. Section 7 puts our results into a quantitative exercise and explores the importance of our mechanism for welfare effects. Section 8 concludes.

2 Background on India's de-reservation policy

Since the 1950s, India has focused on developing its small-scale industry (SSI) sector, which accounts for nearly 40% of the gross industrial value added and stands as the second-largest employer after agriculture.[4] The government believed that SSIs would generate employment and thus absorb surplus labor in the economy (Mohan, 2002). Starting in

[4]Development Commissioner, Ministry of Micro, Small, and Medium Enterprises, India (2018). Available at http://www.dcmsme.gov.in/publications/reserveditems/resvex.htm. Accessed on: 10.07.2024

1967, the government introduced the reservation policy, under which certain products were exclusively reserved for production by SSIs. Initially, only 47 products were reserved, but by 1996 the number had increased to more than a thousand (Martin et al., 2017). Hussain (1997) and Mohan (2002) note that the reserved products were chosen arbitrarily, with no particular selection criterion other than the ability of SSIs to manufacture such items. As stated by the Ministry of Micro, Small and Medium enterprises: *"The main rationale for reservation of items for exclusive production in the SSI sector were the feasibility of producing an item in the SSI Sector without compromising on quality; level of employment generation, diffusion of entrepreneurial talent and prevention of economic concentration"*.[5]

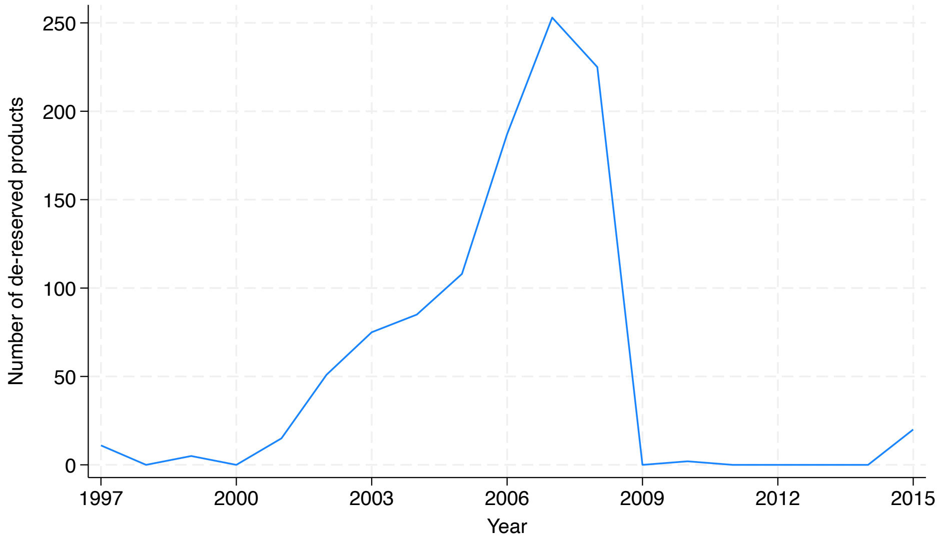
SSIs were initially defined as industrial enterprises with fixed assets not exceeding Rs. 500,000 and fewer than 50 employees. Over time, the employment requirement was removed, and the investment ceiling was raised. By 1999, industrial units with plant and machinery worth up to Rs. 10 million were classified as SSIs. The larger firms already manufacturing the reserved products were allowed to continue, but their output was capped.

Although India began liberalizing its economy in 1991 as part of an IMF adjustment program, the reservation policy remained in place until the late 1990s. Following trade liberalization, SSIs faced competition from imported goods, and larger companies present in the reserved product market were able to exercise monopoly power as most other producers were small. In addition, increasing consumer demand for quality products and continuous technological advances made it difficult for SSIs to produce many items efficiently. Therefore, the Advisory Board appointed a special committee to review the reservation list (Hussain, 1997). The main criteria, based on which de-reservation was recommended, among others, are (i) the feasibility of manufacturing quality products by SSI, (ii) the necessity for higher R&D investments as new products emerged on the market, (iii) safety and hygiene considerations, (iv) export potential, and (v) better utilization of available resources.

Product de-reservation commenced in 1997 with 15 products being de-reserved. Large-scale de-reservation began in 2002 with 51 products and continued through 2008, when 225 products were de-reserved. Between 2000 and 2008, 999 products, or 96% were de-reserved. The last 20 products were de-reserved in 2015. Figure 1 plots the number

[5] Available at: https://dcmsme.gov.in/publications/reserveditems/itemrese.htm#list. Accessed on: 28.11.2024

Figure 1: Number of newly de-reserved products at a given time.



Note: Data on de-reserved products from Martin et al. (2017).

of newly de-reserved products each year. The consensus in the literature is that the de-reservation policy was not systematically related to industry characteristics and that the choice of products to be selected for reservation is somewhat arbitrary (Boehm et al., 2022). We follow this consensus and use the de-reservation of a product as an exogenous shock (Martin et al., 2017).

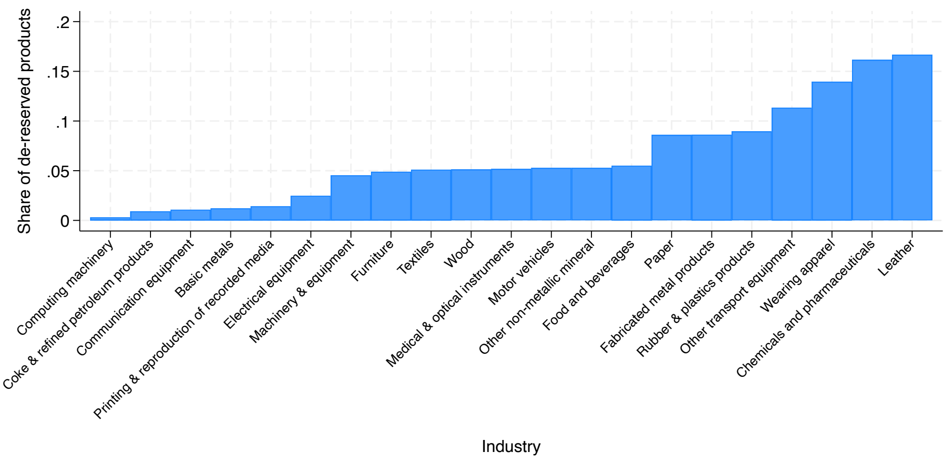
There is considerable industry-wise heterogeneity in the number of de-reserved products. Figure 2 shows that the leather industry has the highest share of de-reserved products relative to the total number of products produced, followed by the chemicals and pharmaceutics industry. On the contrary, computing machinery and the manufacturing of coke and refined petroleum products have the lowest share of de-reserved products.[6]

3 Empirical facts

We proceed by documenting novel empirical facts on the effects of the de-reservation policy and the role of management practices for Indian firms. First, we show that the de-reservation policy led to the entry of new firms into the de-reserved products and resulted in increased competition. As a result, entrants increased their output and product scope, whereas incumbents decreased it. In addition, we document that firms with better

[6] Appendix Figure A.1 presents the total number of de-reserved products by industry.

Figure 2: Share of de-reserved products by industry.



Note: Data on de-reserved products from 1997 to 2015 from Martin et al. (2017). 2-digit industry is defined according to the National Industrial Classification 1998.

management practices have higher output per product, which will guide how we include management practices into the theoretical model.

Data - For our analysis, we use panel data on manufacturing establishments in India from the Annual Survey of Industries (ASI), collected by the Ministry of Statistics and Program Implementation of the Government of India. The ASI is the main source of industrial statistics on the formal manufacturing sector and consists of two parts: (i) a census of all manufacturing establishments that employ more than 100 workers, and (ii) a random sample of establishments that employ between 20 and 100 workers (between 10 and 100 workers for establishments that use power). Note that while the ASI samples establishments, we refer to them as firms throughout the paper. Because the ASI sampling methodology and product classification have changed multiple times, we follow Boehm et al. (2022) and focus on the time period between 2000 and 2008 to ensure consistency in product codes.

The ASI has two unique features that make it particularly suitable for our analysis. First, firms are required to report the revenue and quantities of products manufactured. Product codes are reported using the ASI Commodity Codes (ASICC) at the 5-digit level. Examples of products include wooden chairs (ASICC 51207), harvesters (ASICC 76115), and knitted fabrics (ASICC 63323). To map the ASICC codes to the de-reserved products, we follow the concordance created by Martin et al. (2017). Second, the ASI has a larger coverage of manufacturing firms relative to another widely used dataset for India, the

Prowess database. Furthermore, Prowess focuses mostly on larger firms, making it not well-suited to study policies that affect small-scale firms.

Besides product-level information, the ASI reports standard performance indicators, such as output, number of employees, and industry. We deflate output by the wholesale price index (WPI) for the appropriate product category, capital by the WPI for plant and machinery, and wages by the consumer price index. Industry is defined according to the National Industrial Classification (NIC), with 1998 as the base year.

Empirical strategy - For identification, we use a difference-in-differences approach, comparing the period before and after the de-reservation. To classify whether establishments produce reserved or de-reserved products, we consider all products that they produce, not only their main product. Any product that was ever on the reserved list is defined as a reserved product, and establishments that ever produce such a product are assigned a main reserved product. For 39,225 or 92% of establishments, this procedure identifies a single reserved product, which is fixed over time. For the remaining establishments with multiple reserved products, we assign the product with the earliest year of de-reservation; in 40% of these cases, all reserved products are de-reserved in the same year. Treatment status is captured by an indicator that switches from zero to one in the year the assigned reserved product is de-reserved and remains one thereafter.

Moreover, as in Martin et al. (2017), we decompose the effect for incumbents and entrants. Specifically, throughout the paper, we classify a firm i as an incumbent if its main product was a reserved product before it became de-reserved. Analogously, we define a firm i as an entrant if its main product was a reserved product after de-reservation, but was never produced before it became de-reserved.

Fact 1: Competition increased in de-reserved products - In our first fact, we show that competition increased in de-reserved products. For this, we show that de-reservation spurred the entry of firms into the de-reserved products. We estimate the following two equations to look at product entry:

$$Added_{ijt} = \alpha + \beta Post_{it} + \delta Post_{it} \times Reserved_j + \phi_j + \eta_i + \tau_t + \varepsilon_{it} \quad (1)$$

$$\begin{aligned} Added_{ijt} = {} & \alpha + \beta_1 Incumbent_i \times Post_{it} + \beta_2 Entrant_i \times Post_{it} \quad (2) \\ & + \delta_1 Incumbent_i \times Post_{it} \times Reserved_j + \delta_2 Entrant_i \times Post_{it} \times Reserved_j \\ & + EntryYear_i \times \tau_t + \phi_j + \eta_i + \tau_t + \varepsilon_{ijt} \end{aligned}$$

where $Added_{ijt}$ is a dummy variable taking the value of one if a product j is added by firm i at time t.[7] $Post_{it}$ is a dummy variable switching to 1 when a firm's main reserved product has been de-reserved. $Reserved_j$ is a binary indicator variable that equals 1 if the product has ever been reserved. We add three set of fixed effects: ϕ_j are product fixed effects that absorb time-invariant product-specific characteristics, η_i are firm fixed effects that absorb firm-specific time-invariant differences and allow us to interpret the results as within-firm changes, and τ_t are time fixed effects that absorb a time-specific shocks common to all firms. Standard errors are clustered at the firm level. Equation (1) is estimated on the pooled sample of all firms, whereas equation (2) differentiates between entrant and incumbent firms. $Incumbent_i$ and $Entrant_i$ are dummy variables as indicated above.

To address the concern that firms entering a new product may be fundamentally different from those that did not, we control for the interaction term between the year a firm switched its main product, $EntryYear_i$, and time dummies. This creates non-parametric, time-varying controls that absorb any unobserved characteristics that could potentially explain a firm's decision to switch to a new product space each year. Incumbent firms produce, on average, 2.15 products, with a median incumbent firm producing 1 product. A median entrant, in contrast, produces 2 products.

Estimation results are presented in Table 1. Results in Column (1) show that firms are less likely to add products following the de-reservation of their main product, on average. This is in line with the existing literature, showing that increased competition encourages multi-product firms to become "leaner and meaner" and focus on core products (Eckel and Neary, 2010). In Column (2), we show that this effect is driven by the products that were ever reserved. This result is robust to including firm-year fixed effects in Column (3).

[7] This refers to any product being added, not necessarily the main product.

Looking at incumbents and entrants, we observe that incumbents drive this negative effect, whereas entrants are more likely to add products that were reserved. Hence, after the de-reservation, entrants are significantly more likely to add products that were reserved, while incumbents, faced with tougher competition, became less likely to add products that were reserved. This results in changes in the product entry decision for both incumbents and entrants.

Table 1: Stylized facts at the product-level.

	(1) $Added_{ijt}$	(2) $Added_{ijt}$	(3) $Added_{ijt}$	(4) $Added_{ijt}$	(5) $Added_{ijt}$	(6) $Added_{ijt}$
$Post_{it}$	-0.015**	0.010				
	(0.007)	(0.007)				
$Post_{it} \times reserved_j$		-0.070***	-0.061***			
		(0.010)	(0.013)			
$Incumbent_i \times Post_{it}$				-0.027***	0.005	
				(0.007)	(0.008)	
$Entrant_i \times Post_{it}$				0.072***	0.060***	
				(0.016)	(0.017)	
$Incumbent_i \times Post_{it} \times reserved_j$					-0.080***	-0.075***
					(0.011)	(0.015)
$Entrant_i \times Post_{it} \times reserved_j$					0.042***	0.035*
					(0.016)	(0.019)
N	186,089	186,089	147,782	186,089	186,089	147,782
R-squared	0.402	0.402	0.517	0.421	0.422	0.517
i	✓	✓		✓	✓	
j	✓	✓	✓	✓	✓	✓
t	✓	✓		✓	✓	
$i \times t$			✓			✓

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: The table reports firm-product-level regressions specified in equations (1) and (2). The outcome variable is a binary indicator taking the value of one when the product j is added by firm i at time t. $Post_{it}$ is a binary indicator taking the value of one when a firm's main reserved product has been de-reserved. $Incumbent_i$ is a binary indicator taking the value of one if a firm i's main product was a reserved product before it became de-reserved. $Entrant_i$ is a binary indicator that takes the value of one if a firm i's main product was a reserved product after de-reservation, but was never produced before it became de-reserved. $Reserved_j$ is a dummy indicator for whether or not the product j is reserved. Columns (1), (2), (4), and (5) include firm, product, and year fixed effects. Columns (3) and (6) include product, firm-year fixed effects. Standard errors are clustered at the firm level.

Given that our identification strategy exploits the differential timing in the de-reservation policy, a potential concern that arises is whether de-reserved products were strategically chosen based on their market potential. The appointed committee named export potential and higher R&D requirements as criteria based on which the de-reservation policy was implemented. Hence, it is possible that the product market for earlier de-reserved products was trending in a systematically different way relative to later de-reserved and non-reserved products. This may lead to a violation of the parallel trends assumption. To account for that, we create an event-time variable that captures all periods before and after de-reservation. Thus, the variable takes the value of -1 one period before de-reservation, 0 in the year of de-reservation, 1 in the following year, and so on. This variable is set to zero for firms that do not produce a reserved product. In this way, we can control for any pre-existing linear trends in product markets. Results in Appendix Table B.1 show that our estimates remain practically unchanged when controlling for the event-time trend.

In addition to firm entry into products, we also show that when a product was de-reserved, the total number of firms producing the product increased, which is another indicator of an increase in competition. For that, we calculate the total number of firms producing a specific product in a given year, as well as the number of incumbent firms and entrant firms producing a given product in a given year. Because firms do not produce all products in all years, resulting in the presence of zeros in the dataset, we apply the inverse hyperbolic sine (arcsinh) transformation. This transformation approximates the natural logarithm while preserving zeros in the data (Bellemare and Wichman, 2020). Results presented in Table 2 show that following the de-reservation, the number of firms producing a given product has increased by 13.6%. Decomposing this effect into entrants and incumbents, we see that the number of firms producing a product before de-reservation has declined, whereas there is a statistically significant increase in the number of firms that produce a product after it was de-reserved. Results using the logarithmic transformation are presented in Appendix Table B.2 and are robust.

Fact 2: Entrants increased output and product scope, whereas incumbents decreased it - Next, we proceed by looking at changes in output and product scope at the firm level. We estimate the following regression equations:

$$Y_{it} = \alpha + \beta_1 Post_{it} + \eta_i + \tau_t + \varepsilon_{it} \tag{3}$$

$$\begin{aligned} Y_{it} = \alpha &+ \beta_1 Incumbent_i \times Post_{it} + \beta_2 Entrant_i \times Post_{it} \\ &+ EntryYear_i \times \tau_t + \eta_i + \tau_t + \varepsilon_{it} \end{aligned} \tag{4}$$

Table 2: Number of firms at the product-level.

	(1) $\#Firms_{jt}$	(2) $\#IncumbentFirms_{jt}$	(3) $\#EntrantFirms_{jt}$
$Post_{jt}$	0.136**	-0.810***	4.562***
	(0.055)	(0.173)	(0.437)
N	29,540	29,540	29,540
R-squared	0.009	0.039	0.470
j, t	✓	✓	✓

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: The table reports product-level regressions of the number of firms producing a given product on the de-reservation indicator. We estimate the following equation: $Y_{jt} = \alpha + \beta_1 Post_{jt} + \phi_j + \tau_t + \epsilon_{it}$. The outcome variables are transformed using the inverse hyperbolic sine (arcsinh) transformation. $\#IncumbentFirms_{jt}$ is the number of firms that produce a given product before it was de-reserved. $\#EntrantFirms_{jt}$ is the number of firms producing a given product after it was de-reserved. $Post_{jt}$ is a binary indicator taking the value of one when a product j is de-reserved at time t. Standard errors are clustered at the product level.

where Y_{it} is the log of total output or the log number of products. All other variables are defined as above.

Results of the regressions (3) and (4) are presented in Table 3 and show that, on average, the total output has increased significantly after de-reservation by 2.3%. This effect is driven by a 23% increase in total output for entrants, whereas there is no statistically significant effect for incumbents.

Looking at the number of products, we document that firms produce 1.2% fewer products after de-reservation. This is consistent with the literature on competition and product choice of multi-product firms (Mayer et al., 2014; Tewari and Wilde, 2019). The aggregate effect masks substantial heterogeneity when looking at incumbents and entrants. Whereas the number of products produced by incumbents decreases significantly after de-reservation, entrants produce 12% more products, on average. This is consistent with our previous finding that entrants are more likely to add a reserved product after de-reservation. These results are robust to controlling for an event-trend as presented in Appendix Table B.3.

Fact 3: Output per product is positively related to management practices - To verify if there is a correlation between management practices and firm performance, we present a correlation plot of output per product and the management practices score (MPS) measure from the World Management Survey (WMS) constructed by Bloom et al. (2012), which is a measure for management quality widely used in the literature. We

Table 3: Stylized facts at the firm-level.

	(1) ln(output)	(2) ln(# products)	(3) ln(output)	(4) ln(# products)
$Post_{it}$	0.023*	-0.012**		
	(0.012)	(0.006)		
$Incumbent_i \times Post_{it}$			-0.019	-0.033***
			(0.013)	(0.006)
$Entrant_i \times Post_{it}$			0.230***	0.116***
			(0.032)	(0.016)
N	234,013	201,734	234,013	201,734
R-squared	0.930	0.818	0.930	0.819
i, t	✓	✓	✓	✓

Standard errors in parentheses

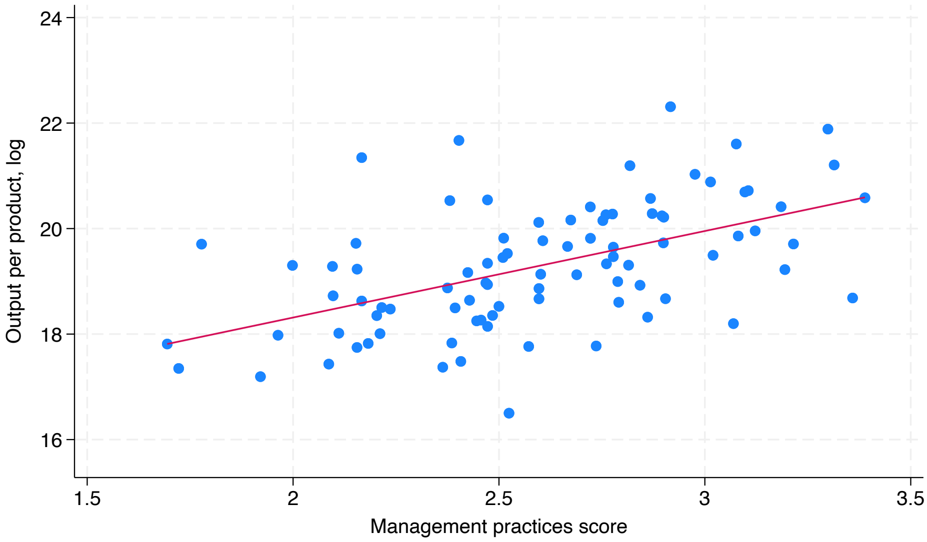
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: The table reports firm-level regressions specified in equations (3) and (4). The outcome variable is the log of output by firm i at time t, and the log number of products. $Post_{it}$ is a binary indicator taking the value of one when a firm's main reserved product has been de-reserved. $Incumbent_i$ is a binary indicator taking the value of one if a firm i's main product was a reserved product before it became de-reserved. $Entrant_i$ is a binary indicator that takes the value of one if a firm i's main product was a reserved product after de-reservation, but was never produced before it became de-reserved. Columns (1) and (4) include firm and year fixed effects. Standard errors are clustered at the firm level.

construct bins of 2-digit industry and employment categories for (i) 50-100, (ii) 101-250, (iii) 251-500, (iv) 501-1000, and (v) 1000+ employees. Figure 3 shows that there is a positive relationship between the management practices score and output per product. We interpret this as an indication that firms with better management practices tend to focus on a limited number of products, while firms with poor management practices tend to keep low-performing products.

The three facts presented in this section point to (i) an increase in competition after de-reservation, (ii) a negative effect of de-reservation on incumbent firms, and (iii) a positive relationship between management practices and output per product. We will use these three facts to incorporate the de-reservation policy and management practices into a theoretical model. The model will allow us to (i) derive predictions about the heterogeneous effect of the de-reservation policy depending on firms' management practices, (ii) study the underlying mechanisms, and (iii) structurally derive a firm-level measure of management practices.

Figure 3: Correlation between management practices score and output per product.



Note: Correlation graph between the average management score and log output per product. Management score data is taken from the World Management Survey constructed by Bloom et al. (2012). Bins are 2-digit industry and employment categories for (i) 50-100, (ii) 101-250, (iii) 251-500, (iv) 501-1000, and (v) 1000+ employees.

4 Model

This section develops a partial equilibrium model with multi-product firms in multiple sectors.[8]

Consumers - The economy is populated by a continuum of L consumers with preferences given by the following utility function:

$$U_t = \sum_s \kappa_s \log U_{st} \tag{5}$$

$$U_{st} = \left(\int_{i \in \Lambda_s} \int_{j \in \Omega_{is}} q_{isjt}^{\frac{\sigma-1}{\sigma}} \, dj \, di \right)^{\frac{\sigma}{\sigma-1}}, \tag{6}$$

where s denotes sectors, i denotes firms, and j denotes products. Λ_s is the set of firms active in sector s and Ω_{is} is the set of products produced by the firm i in sector s. σ is the elasticity of substitution between any two products within a sector. We assume $\sigma > 1$ and $\sum_s \kappa_s = 1$.

In what follows, we focus on just one sector. From the consumer's utility maximization

[8]The model is in partial equilibrium because it abstracts from wages and the number of firms is exogenous. However, we allow the price index to adjust when simulating the model in section 7.

problem, the optimal aggregated demand for each product is:

$$q_{isjt} = \kappa_s E_t P_{st}^{\sigma-1} p_{isjt}^{-\sigma}, \tag{7}$$

where q_{isjt} and p_{isjt} are, respectively, the quantity and price of product j from firm i, E_t is total expenditure, and $P_{st} = \left(\int_{i\in\Lambda_s} \int_{j\in\Omega_{is}} p_{isjt}^{1-\sigma} dj di \right)^{\frac{1}{1-\sigma}}$ is the sector price index.

Firms - An exogenous number of firms are active in each sector, with firms only being able to produce the products in their respective sectors. Each firm possesses an exogenous amount of organizational capital, which is fixed over time.

We assume that organizational capital can be used to decrease a firm's marginal costs. In our model, we follow Nocke and Yeaple (2014) in that organizational capital can be interpreted as a managerial input that (i) is in fixed supply within the firm and (ii) cannot be shared across products. This implies that the more of it that is allocated to one product, the less can be allocated to another. In practice, it is classified as an intangible asset and is considered a major production factor (Brynjolfsson et al., 2002).[9] Carlin et al. (2012) and Hasan et al. (2018) argue that acquiring organizational capital necessitates a significant investment of time, as it relies on the accumulation of learning and experience, such as employee training or investments into R&D. Consequently, it is not feasible to achieve substantial improvements in organizational capital within a short time horizon and, for simplicity, we consider organizational capital to be fixed over time in our model.

The firm faces the following constraint when allocating organizational capital across products:

$$\int_{j\in\Omega_{is}} o_{isjt} dj \leq \mathcal{O}_i, \tag{8}$$

where $o_{isjt} \geq 0$ is the organizational capital allocated by firm i to produce product j and $\mathcal{O}_i > 0$ is the total organizational capital available to firm i.

Firms also possess an exogenous firm-level productivity, randomly drawn from a distribution $F(Z)$. We allow firm-level productivity to change over time through unexpected, independent, and identically distributed shocks. Moreover, firms receive time-invariant productivity draws for all products from a Pareto distribution $G(z) = 1 - z^{-\gamma_s}$ with

[9] Section 5.1 describes how we measure organization capital in the data.

$\gamma_s > \sigma - 1 \ \forall s$. The marginal cost of a firm i producing a product j is:

$$c_{isjt} = \frac{1}{Z_{it} z_{isj} o_{isjt}^{\theta_i}}, \tag{9}$$

where Z_{it} is the firm-level productivity draw of firm i and z_{isj} is the productivity draw of firm i for product j. The parameter θ is a term that represents firm-specific management practices: firms with higher (lower) values of θ have better (worse) management practices. Firms draw θ from a distribution $H(\theta)$ with support $(0, 1/(\sigma - 1))$, and we assume $\theta_i < 1/(\sigma - 1) \ \forall i$.[10] We think of management practices as a technology or knowledge that influences the efficiency with which organizational capital is used within the firm.

Given the consumers' demand in equation (7), the firm charges a price that is a constant markup over marginal costs:

$$p_{isjt} = \frac{\sigma}{\sigma - 1} c_{isjt}. \tag{10}$$

Finally, combining demand, marginal cost, and price, the profit from producing a product is:

$$\pi_{isjt} = E_{st} P_{st}^{\sigma-1} Z_{it}^{\sigma-1} z_{isj}^{\sigma-1} o_{isjt}^{\theta_i(\sigma-1)}, \tag{11}$$

where $E_{st} = \sigma^{-\sigma}(\sigma - 1)^{\sigma-1} \kappa_s E_t$ is a sector demand shifter.

The Firm Problem - The firm chooses which products to produce and how to allocate its limited organizational capital across products, subject to the consumers' demand in equation (7) and taking into account the constraint from equation (8) and its optimal price in equation (10). For this, each firm solves the following maximization problem:

$$\max_{\{o_{isjt}\}} \Pi_{it} = \int_{j \in \Omega_{is}} \pi_{isjt} - f \, dj, \tag{12}$$

where f is a fixed cost incurred by the firm for each additional product it chooses to produce. Using the overall endowment of organizational capital in equation (8), the

[10]Note that in the case were $\theta_i(\sigma - 1) = 1 \ \forall i$, firms would choose to allocate all their organizational capital to a single product and the model boils down to a Melitz type of model with single-product firms.

optimal allocation across products is the following:

$$o_{isjt} = \frac{\mathcal{O}_i}{B_{it}} z_{isj}^{\frac{\sigma-1}{1-\theta_i(\sigma-1)}}, \tag{13}$$

where we interpret $B_{it} = \int_{j\in\Omega_{is}} z_{isj}^{\frac{\sigma-1}{1-\theta_i(\sigma-1)}} dj$ as the overall organizational strain of the firm, that is, a higher B_{it} indicates a higher degree of competition for organizational capital between products within firm i. B_{it} increases if a firm produces more products or products with higher productivity.

Because organizational capital is fixed for the firm, there is a trade-off between the firm's decision to expand its product range and lower its marginal cost of producing each product. The firm's management practices dictate how pronounced this trade-off is: better management practices increase the effectiveness of organizational capital in reducing products' marginal costs, thus increasing the opportunity cost of introducing an additional product.[11]

Due to the fixed cost per product, the firm will produce only a subset of all available products. Since revenues and profit are increasing in the productivity draw of a product, a sorting pattern arises in which the firm produces all products above a certain productivity threshold $\underaccent{\tilde}{z}$. Hence, the firm decides the optimal set of products to produce by choosing $\underaccent{\tilde}{z}$, considering the optimal allocation of organizational capital across products in equation (13). The maximization problem, in which we rewrite the problem from choosing the optimal set of products into one where the firm chooses a productivity threshold, is the following:

$$\max_{\{\underaccent{\tilde}{z}_{ist}\}} E_{st} P_{st}^{\sigma-1} Z_{it}^{\sigma-1} \mathcal{O}_i^{\theta_i(\sigma-1)} B_{it}^{1-\theta_i(\sigma-1)} - f(1 - F(\underaccent{\tilde}{z}_{ist}))M_s, \tag{14}$$

where M_s is the number of products that can be produced in sector s, i.e. $M_s = |\Omega_s|$. The first order conditions associated with equation (14) implies the following productivity threshold:

$$\underaccent{\tilde}{z}_{ist} = \left[\frac{(\gamma_{1is}M_s)^{\theta_i(\sigma-1)} f}{(1-\theta_i(\sigma-1))E_{st}P_{st}^{\sigma-1}Z_{it}^{\sigma-1}\mathcal{O}_i^{\theta_i(\sigma-1)}}\right]^{\frac{1}{(\sigma-1)(1+\gamma_s\theta_i)}}, \tag{15}$$

where $\gamma_{1is} = \frac{\gamma_s}{\gamma_s - \frac{\sigma-1}{1-\theta_i(\sigma-1)}}$.

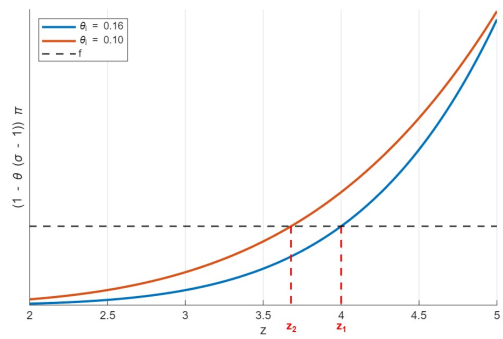
As can be seen in equation (15), the productivity threshold depends on, among others,

[11] A similar trade-off exists in Nocke and Yeaple (2014).

the supply of organizational capital within the firm, the sector price index, and the overall expenditure in the sector. If organizational capital is scarce in the firm ($\mathcal{O}_i$ is lower), the firm reduces the range of products by increasing the productivity threshold. A higher fixed cost per product (f is higher) has a similar effect. Equation (15) also shows the relationship between management practices and the product range. At higher levels of management practices, the firm produces fewer products by concentrating its organizational capital on the most productive products. At the limit, as $\theta_i(\sigma - 1)$ converges to one, $\underset{\sim}{z}_{ist}$ moves towards infinity, and the firm produces only its most productive product.

After solving for $\underset{\sim}{z}_{ist}$, we can solve the integral in B_{it} and calculate the amount of o_{isjt} that the firm allocates depending on the product productivity z_{isj}. Figure 4 shows the profits per product for two different levels of θ_i, with $\underset{\sim}{z}_{ist}$ corresponding to the product that produced by the firm with the lowest productivity z_{isj}. Note that FOC condition from the maximization problem in (14) implies $(1 - \theta_i(\sigma - 1))\pi(\underset{\sim}{z}_{ist}) = f$, that is, the firm takes into account that producing product $\underset{\sim}{z}_{ist}$ means reducing the amount of organizational capital that can be allocated to all other products. That is, there is a supply-sided cannibalization effect, which is larger in firms with better management practices. As can be seen in the figure, better management practices increase the slope of the profit function. As the slope increases, the profit of products with low productivity decreases, which causes the productivity threshold to be higher, z_1 instead of z_2 in the figure. In other words, everything else equal, a firm with better management practices will produce fewer products, but will have a higher profit in its most productive products.[12]

Figure 4: Profit per product.



Note: Profit per product depending on its productivity z. We assume $P_{st} = E_{st} = 1$, $Z_i = 4$, $\sigma = 4$, $O_i = 5$, $M_s = 50$, and $\gamma_s = 6$.

[12]Note that π_{isjt} depends on f through its effect on B_{it}, such that shifting f in the figure also shifts the π_{isjt} curves.

After substituting equation (15) into equation (14), the overall profit of a firm across all products can be rewritten as:

$$\Pi_{it} = X_{1ist}\mathcal{O}_i^{\frac{\gamma_s\theta_i}{1+\gamma_s\theta_i}}, \tag{16}$$

where $X_{1ist} = \left(E_{st}^{\frac{1}{\sigma-1}} Z_{it} P_{st}\right)^{\frac{\gamma_s}{1+\gamma_s\theta_i}} f^{1-\frac{\gamma_s}{(\sigma-1)(1+\gamma_s\theta_i)}} M_s^{\frac{1}{1+\gamma_s\theta_i}} \left[\frac{(\gamma_{1is})^{\theta_i(\sigma-1)}}{(1-\theta_i(\sigma-1))}\right]^{-\frac{\gamma_s}{(\sigma-1)(1+\gamma_s\theta_i)}} \left(\frac{\gamma_{1is}}{(1-\theta_i(\sigma-1))} - 1\right)$. Hence, firms with better management practices have higher overall profits.

4.1 The de-reservation policy

In the model, the de-reservation policy implies an exogenous increase in the number of firms in sector s.[13] The increase in the number of firms causes an endogenous decrease in the sector price index, P_{st}.

Incumbents - Firms active in sector s before de-reservation are affected by a decrease in the sector price index due to the increased competition. We summarize the effect of de-reservation on incumbents in proposition 1.

Proposition 1. *De-reservation reduced the revenue and number of products for incumbent firms, and the effect is decreasing (in absolute terms) in management practices θ_i. Specifically, if $\varepsilon_{R,P} \equiv \left|\frac{\partial R_{it}}{\partial P_{st}}\frac{P_{st}}{R_{it}}\right|$ and $\varepsilon_{N,P} \equiv \left|\frac{\partial N_{it}}{\partial P_{st}}\frac{P_{st}}{N_{it}}\right|$, then:*

$$\varepsilon_{R,P} = \varepsilon_{N,P} = \frac{\gamma_s}{1+\theta_i\gamma_s} > 0 \qquad \textit{and} \qquad \frac{\partial \varepsilon_{N,P}}{\partial \theta} = \frac{\partial \varepsilon_{R,P}}{\partial \theta} = -\frac{\gamma_s^2}{(1+\theta_i\gamma_s)^2} < 0.$$

Proof: See Appendix D.

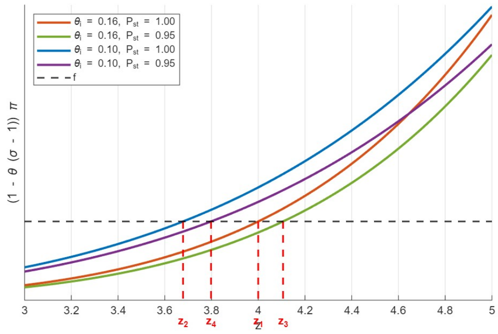
Proposition 1 indicates that a decrease in the sector price index causes a revenue drop for all incumbent firms. Furthermore, the elasticity of revenue to the sector price index increases with the Pareto shape parameter and decreases with the firm's management practices. The numerator is the degree of product heterogeneity: a high γ_s indicates that products are very homogeneous (i.e., the productivity distribution has a thin tail) and the productivity threshold is in a region with a large mass of products. In this case, any movement of the productivity threshold leads to a larger change in products produced

[13] One could model a free-entry condition and endogenize the number of firms. However, treating the number of firms as exogenous provides a closer link to the simulation section, as what we observe in the data is the increase in the number of firms, not the cost of entry.

and revenues. The denominator, $1 + \theta_i\gamma_s$, is the degree to which the firm's management practices distort the productivity distribution, and it is one if θ_i is zero. Finally, the elasticity of the number of products to the price index is the same as the elasticity of revenue to the price index.

This result relies on how θ_i affects firms' marginal cost. Firms with better management practices concentrate their organizational capital on their top products, which causes the distribution of the marginal cost of products to become steeper. In our model, tougher competition forces firms to focus on their most productive products and reduce their product scope. This can be seen in Figure 5, which shows the change in the profit per product and productivity thresholds after a decrease in P_{st} in firms with different levels of θ_i. There, we can see that decreasing P_{st} shifts the profit curve down for all products, and the shift is very similar for both θ_is. The productivity thresholds for both firms increase, from z_1 to z_3 and from z_2 to z_4. However, the steeper profit per product curve of firms with high θ_i relative to firms with low θ_i means that (i) the products that fall below the threshold represent a lower share of profit and (ii) the relative change in profits per product is lower.

Figure 5: Profit per product, a decrease in P_{st}.



Note: Profit per product depending on its productivity z. We assume $E_{st} = 1$, $Z_i = 4$, $\sigma = 4$, $O_i = 5$, $M_s = 50$, and $\gamma_s = 6$.

Another way of looking at the intuition behind proposition 1 is that firms with better management practices have a comparative advantage in specializing in their most productive products. After an increase in competition, all firms reduce their product scope and focus their organizational capital on the products at the tail of the productivity distribution. However, this reduction is relatively smaller for firms with better management practices, as they were already specialized in producing a smaller range of products.

Both explanations of the mechanism rely on the productivity differences across products, and the mechanism disappears if firms are equally able to produce all products. As the main driver of the heterogeneous effect is the extent to which firms can specialize in producing certain products, the degree of product heterogeneity γ_s also influences the intensity of the mechanism.

Entrants - The model is not informative about the effect of de-reservation on entrants, as we do not model firms before they enter.[14] However, we show in Table 3 that, after de-reservation, new entrants increased their output and product scope, which in our model could be associated with a permanent increase in the firm-level productivity of these firms. Hence, we define entrants as firms that face an increase in Z_{it} as well as a decrease in the sector price index P_{st}. We summarize the effect of an increase in Z_{it} on firms in lemma 1.

Lemma 1. *An increase in productivity Z_{it} increases the revenues and number of products of firms, and the effect is decreasing (in absolute terms) in management practices θ_i. Specifically, if $\varepsilon_{R,Z} \equiv \left|\frac{\partial R_{it}}{\partial Z_{it}}\frac{Z_{it}}{R_{it}}\right|$ and $\varepsilon_{N,Z} \equiv \left|\frac{\partial N_{it}}{\partial Z_{it}}\frac{Z_{it}}{N_{it}}\right|$, then:*

$$\varepsilon_{R,Z} = \varepsilon_{N,Z} = \frac{\gamma_s}{1+\theta_i\gamma_s} > 0 \qquad \textit{and} \qquad \frac{\partial \varepsilon_{N,Z}}{\partial \theta} = \frac{\partial \varepsilon_{R,Z}}{\partial \theta} = -\frac{\gamma_s^2}{(1+\theta_i\gamma_s)^2} < 0.$$

Proof: See Appendix D.

Given the opposing effects of proposition 1 and lemma 1, the model cannot predict how de-reservation will affect entrants, especially as we lack information on the relative size of both effects for each entrant. Furthermore, entrants are those firms that change their main product after de-reservation, which indicates a product-level reallocation of resources not entirely captured in lemma 1. Such a within-firm across-products reallocation is likely to have a stronger effect on firms with better management practices, as they gain the most from specializing in a few highly productive products. All these effects are summarized in corollary 1.

Corollary 1. *The net effect of de-reservation on the revenues and number of products for entrant firms is ambiguous and depends on the overall changes in the price index, firm-level productivity, and within-firm reallocation. The heterogeneity of the effect with respect to management practices is also ambiguous.*

[14] We could model two distinct types of firms in the model, incumbents and entrants, but the problem remains that we cannot model from which sector these entrants are originally and which conditions they faced there.

Sector heterogeneity - As can be seen in proposition 1 and lemma 1, the importance of management practices is linked to the Pareto shape parameter of the product productivity distribution, γ_s. The intuition is that higher γ_s leads to lower dispersion in product productivity. This, in turn, means that fewer products have high productivity, with a large mass of products having relatively low values of z, which decreases the organizational strain of the firm B_{it} and increases the amount of organizational capital per product. Finally, the larger organizational capital per product increases the importance of θ. This brings us to the following corollary:

Corollary 2. *The heterogeneous effect of de-reservation through differences in management practices θ_i is larger in sectors with higher product productivity dispersion γ_s.*

5 Empirical strategy

The objective of this section is to define an approach to test the predictions of the theoretical model. For this, we first need to estimate organizational capital and management practices, which we do using the ASI data. With the guidance of our theoretical model, this provides us with a firm-level measure of management practices using firms' balance sheet information.

5.1 Measuring Organizational Capital

Measuring a firm's specific organizational capital is challenging due to its partially tacit nature and the lack of detailed reports on organizational capital investments. We follow Lev and Radhakrishnan (2005), Eisfeldt and Papanikolaou (2013), and Peters and Taylor (2017) and use Sales, General, and Administrative (SG&A) expenses as a proxy for firms' investment in organizational capital. SG&A includes expenditures that are not directly related to production but constitute investments in organizational capital, such as technical know-how and consultancy charges, directors' fees, communication charges, audit fees, bank charges, advertising costs, and other non-industrial service expenses. To estimate the stock of organizational capital, $\mathcal{O}_{it}$, we follow Eisfeldt and Papanikolaou (2013) and use the perpetual inventory method. Specifically, we recursively calculate the stock of organizational capital ($\mathcal{O}_{it}$) by cumulating the deflated value of SG&A expenses as:

$$\mathcal{O}_{it} = (1-\delta_0)\mathcal{O}_{it-1} + \frac{SGA_{it}}{CPI_t}. \tag{17}$$

The stock of $\mathcal{O}_{it}$ is measured for each firm i at time t, δ is the depreciation rate, and CPI_t is the consumer price index. To implement the law of motion, the initial stock of $\mathcal{O}_{it}$ is estimated as follows:

$$\mathcal{O}_0 = \frac{SGA_1}{(g+\delta_0)}, \tag{18}$$

where g is the average real growth rate of firm-level SG&A expenses, which is 10% in our sample. We use a depreciation rate of 15% as in Eisfeldt and Papanikolaou (2013).[15] We winsorize SG&A expenses and $\mathcal{O}_{it}$ at 1% and 99% to minimize the effect of outliers.

A valid concern when bringing the model to the data is that firms might have adjusted their organizational capital in response to the de-reservation policy. To test whether this is the case, we regress the changes in organizational capital on the de-reservation indicator. Results reported in Appendix Table B.4 show that the de-reservation policy had no significant effect on the growth of organizational capital. The point estimate is precisely zero, which substantiates our assumption that firms' organizational capital is exogenous, at least in the short run.

5.2 Estimating Management Practices

We estimate management practices using the firm's revenue function from our model:

$$R_{it} = \sigma E_{st} P_{st}^{\sigma-1} Z_{it}^{\sigma-1} \mathcal{O}_{it}^{\theta_i(\sigma-1)} \left(\gamma_{1is} M_s\right)^{1-\theta_i(\sigma-1)} z_{it}^{(\sigma-1)(1+\gamma_s\theta_i)-\gamma_s}, \tag{19}$$

where we have added the t subscript to $\mathcal{O}_{it}$ because our measurement of organizational capital in the data allows it to change over time.[16] Taking logs:

$$\ln(R_{it}) = (\sigma-1)\ln(Z_{it}) + \theta_i(\sigma-1)\ln(\mathcal{O}_{it}) + ((\sigma-1)(1+\gamma_s\theta_i)-\gamma_s)\ln(z_{it}) + \eta_{st} + \eta_i, \tag{20}$$

[15] The results are robust to using alternative depreciation rates, e.g., 10% and 25%. Results are available upon request.

[16] The mechanism of the model depends on organizational capital being difficult to adjust, but not necessarily fixed over time.

where $\eta_{st} = \ln(\sigma E_{st} P_{st}^{\sigma-1})$ and $\eta_i = (1-\theta_i(\sigma-1))\ln(\gamma_{1is}M_s)$. We make use of the following equality: $\theta_i = \theta_s + (\theta_i - \theta_s)$, where θ_s is the average management practices in a sector. Then, the equation above can be rewritten as:

$$\ln(R_{it}) = (\sigma-1)\ln(Z_{it}) + \theta_s(\sigma-1)\ln(\mathcal{O}_{it}) + ((\sigma-1)(1+\gamma_s\theta_s)-\gamma_s)\ln(z_{it}) + \eta_{st} + \varepsilon_{it}, \quad (21)$$

where $\varepsilon_{it} = \eta_i + (\theta_i - \theta_s)(\sigma-1)\ln(\mathcal{O}_{it}) + (\sigma-1)(1+\gamma_s(\theta_i-\theta_s))\ln(z_{it})$. Equation (21) can be estimated for each sector s in our data by using our measurement of $\mathcal{O}_{it}$ and proxies for $\ln(z_{it})$ and Z_{it}. As a proxy for $\ln(z_{it})$, we choose the log of product scope ($ln(\#products_{it})$), that is, the number of products a firm i produced during year t.[17] $\ln(Z_{it})$ is proxied by total factor productivity (TFP) and estimated using the Ackerberg et al. (2015) approach for each 2-digit manufacturing industry, with value added as the outcome variable. Finally, $\ln(R_{it})$ is the total output reported in the ASI by the firm i in year t, $\ln(output_{it})$. Our estimating equation is then:

$$\ln(output_{it}) = \beta_1 \ln(\mathcal{O}_{it}) + \beta_2 \ln(Z_{it}) + \beta_3 \ln(\#products_{it}) + \eta_{st} + \varepsilon_{it}. \quad (22)$$

The residual from the above regression reveals what remains unexplained by the fitted model. One potential problem in equation (22) is that, due to systematic differences in reporting of SG&A expenses, our management practices measure may differ systematically across firms in different industries. To take this into account, we rank firms based on our management practices measure relative to their industry peers. The rank, which we denote as $\hat{\theta}_i$ and ranges between 1 and 5, is assigned based on the firm's quintile of the residual from regression (22) within each 2-digit industry. The higher the rank, the better the firm's management practices within the industry's distribution. Using the rank instead of the calculated management practices measure ensures that the results are driven by within rather than between industry differences in management practices.

Validation - We explore now the validity of our measurement of management practices. For this, we want to show how management practices are related to other firm performance indicators, how management practices are related to the management practices score from Bloom et al. (2012), and whether entrants rank higher than incumbents in our measure

[17]We refer to this variable as N_{it} in the theoretical model.

of management practices. Finally, we also propose three other alternative estimates of management practices.

Table 4 presents the correlation table for our estimated measure of management practices and firm performance indicators. $\hat{\theta}_i$ has a strong positive correlation with a firm's assets, employment, output, and labor productivity. Interestingly, the correlation between $\hat{\theta}_i$ and $\log \mathcal{O}_{it}$, and $\hat{\theta}_i$ and Z_{it} is relatively small in magnitude, indicating that management practices are not to be confused with productivity, although they are positively correlated.

Table 4: Correlation between management score and firm performance measures.

	$\hat{\theta}_i$	$\log \mathcal{O}_{it}$	Z_{it}	log(assets)	log(employment)	log(output)	log(output/employee)
$\hat{\theta}_i$	1						
$\log \mathcal{O}_{it}$	0.0130***	1					
Z_{it}	0.0289***	0.246***	1				
log(assets)	0.310***	0.790***	0.150***	1			
log(employment)	0.341***	0.716***	0.224***	0.689***	1		
log(output)	0.424***	0.819***	0.324***	0.829***	0.781***	1	
log(output/employee)	0.295***	0.506***	0.265***	0.552***	0.130***	0.721***	1

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 6 presents the correlation between $\hat{\theta}_i$ and the average management practices score constructed by Bloom et al. (2012) (Appendix Figure A.2 shows the correlation between θ_i and management practices score). Both plots show that our measure is positively correlated with the established measure of management practices in the literature.[18]

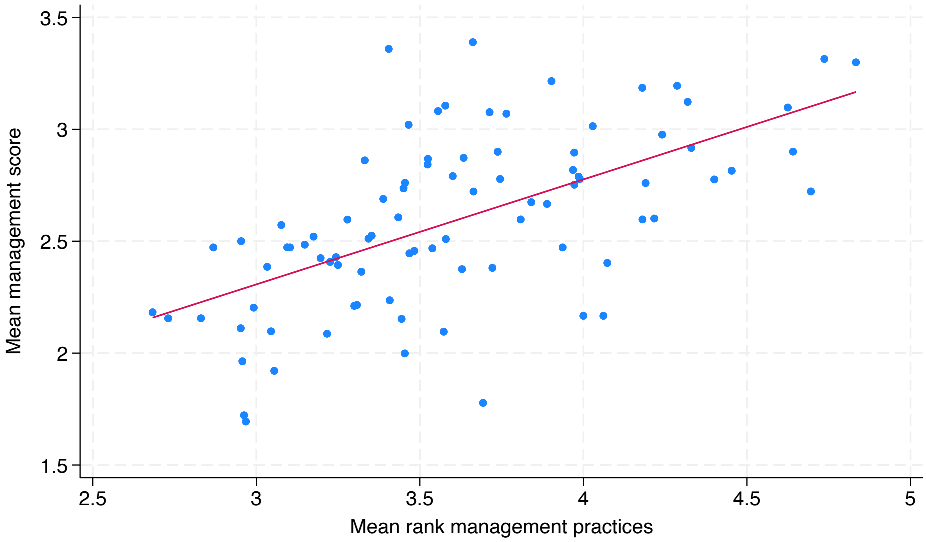
Table 5 presents summary statistics for entrants and incumbents. Entrants are, on average, larger than incumbents in terms of organizational capital, assets, output, and the number of products. Entrants also feature, as one would expect, better levels of management practices relative to incumbents.

Additionally, we provide two alternative estimates of management practices based on equation (22). First, instead of using SG&A to calculate $\mathcal{O}_{it}$, we use the number of days worked by the manager[19] as a proxy for $\mathcal{O}_{it}$. The reasoning behind this proxy is that managers have a fixed amount of time at work and can decide how to distribute their time across products. We then use this proxy for $\mathcal{O}_{it}$ in equation (22), take the residual, and create the rank within industry, which we label $\hat{\theta}_i^{man}$. The correlation between $\hat{\theta}_i$ and

[18]One can argue that the correlation is driven by firm size, as larger firms have better MPS and a higher rank of management practices. To circumvent this, we estimate correlations for each employment category separately. Appendix Figure A.3 shows that a positive correlation exists for each employment category.

[19]The ASI does not report hours worked, only the number of days worked.

Figure 6: Correlation between management score and rank of management practices.



Note: Correlation graph between the average management score and the rank of management practices. Management score data is taken from the World Management Survey constructed by Bloom et al. (2012). Bins are 2-digit industry and employment categories for (i) 50-100, (ii) 101-250, (iii) 251-500, (iv) 501-1000, and (v) 1000+ employees.

Table 5: Summary statistics for incumbents and entrants.

	Incumbents		Entrants	
	mean	sd	mean	sd
$\log \mathcal{O}_{it}$	14.868	2.173	15.181	2.051
$\hat{\theta}_i$	3.061	1.394	3.117	1.427
Z_{it}	8.851	1.325	9.058	1.295
log(assets)	14.835	2.566	15.453	2.194
log(employment)	3.809	1.442	3.945	1.445
log(output)	16.657	2.202	17.048	1.942
log(output/employee)	12.823	1.481	13.089	1.332
# products	2.151	1.950	2.304	1.810

$\hat{\theta}_i^{man}$ is high, of 0.65.

Second, instead of using the estimated TFP in equation (22), we use the value added per worker as a proxy TFP in equation (22). This eases the interpretation of the estimated equation, as we do not use an estimated TFP but rather a proxy for TFP. We label resulting management practices rank as $\hat{\theta}_i^{prod}$. The correlation between $\hat{\theta}_i$ and $\hat{\theta}_i^{prod}$ is 0.93.

We see the high correlation between the different estimations of management practices as a reassuring sign that $\hat{\theta}_i$ is indeed ranking firms based on their management practices. Furthermore, our results remain highly robust if we use $\hat{\theta}_i^{man}$ or $\hat{\theta}_i^{prod}$ instead of $\hat{\theta}_i$.

Given that our variables of interest are output and the number of products, we provide one last measurement of management practices that does not require using output or the number of products. Specifically, we use the intuition from Proposition 1: everything else equal, the output share of the worst product is smaller in firms with better management practices. That is, we regress the following equation:[20]

$$\frac{r_{is\underline{z}t}}{R_{it}} = \beta_1 \ln(\mathcal{O}_{it}) + \beta_2 \ln(Z_{it}) + \eta_{st} + \eta_j + \varepsilon_{it}, \tag{23}$$

where $r_{is\underline{z}t}$ is the output of the smallest product of firm i and η_j are fixed effects that control for the identity of the smallest product. The remaining variables are as explained above. The idea behind this regression is that, conditional on $\mathcal{O}_{it}$, Z_{it}, and the set of fixed effects, the output share of the smallest product in a firm with better management practices will be smaller, which will imply a smaller error term. We change the sign of ε_{it} and follow the same procedure explained in equation (22). The result is a proxy for management practices, denoted by $\hat{\theta}_i^{min}$. Higher $\hat{\theta}_i^{min}$ imply better management practices.

5.3 Estimating Equation

To examine the heterogeneous effects of the de-reservation policy based on management practices, we estimate the following triple differences interaction:

$$Y_{it} = \alpha + \beta_1 Post_{it} + \beta_2 \hat{\theta}_i + \beta_3 Post_{it} \times \hat{\theta}_i + \eta_i + \tau_t + \varepsilon_{it} \tag{24}$$

$$\begin{aligned} Y_{it} = \alpha &+ \delta_1 Incumbent_i \times Post_{it} + \delta_2 Entrant_i \times Post_{it} + \delta_3 \hat{\theta}_i \\ &+ \delta_4 Incumbent_i \times Post_{it} \times \hat{\theta}_i + \delta_5 Incumbent_i \times Post_{it} \times \hat{\theta}_i \\ &+ EntryYear_i \times \tau_t + \eta_i + \tau_t + \varepsilon_{it} \end{aligned} \tag{25}$$

where all variables are defined as above and $\hat{\theta}_i$ is the rank of a firm's management practices measure relative to its industry peers. We include firm and year fixed effects to account for time-invariant differences across firms and time trends common to all firms, respectively. The main coefficients of interest are β_3, which captures the heterogeneous effects of the de-reservation policy on an average firm, and δ_4 and δ_5, which represent the heterogeneous effects of de-reservation based on management practices for incumbents and entrants,

[20] Using $\ln(\frac{r_{iszt}}{R_{it}})$ instead of $\frac{r_{iszt}}{R_{it}}$ do not change our results.

respectively.

6 Results

6.1 Baseline results

Output - The baseline estimation results on output are presented in Table 6. The de-reservation policy had a significant and positive effect on firms' output as presented in Column (1). Column (2) shows that firms with better management practices are associated with greater output. Our main coefficients of interest are presented in Column (3). $\hat{\theta}_i$ is not estimated in Column (3), as it is firm-specific and constant over time and is absorbed by firm fixed effects, but its interaction with $Post_{it}$ is. As predicted by the theory, the total output of a firm with average management practices decreased by 2.4% after the de-reservation policy and a resulting increase in competition.[21] However, firms in the highest quintile of management practices ($\hat{\theta}_i = 5$) experienced an increase in their output of 39.4%, while firms in the lowest quintile of management practices ($\hat{\theta}_i = 1$) observed a decline in output of 32%. This is in line with our model, where firms with better management practices are less negatively affected because they have a comparative advantage to specialize in a smaller range of products with lower marginal costs. Due to this specialization, firms with better management practices are less adversely affected by the increase in competition following the de-reservation.

To ensure that the estimated management practices affect firms differently and do not capture productivity improvements, we control in Column (4) for the level of Z_{it} and the interaction term between Z_{it} and a post-treatment dummy. We observe that Z_{it} is positively associated with output. However, this is not the case that firms with higher Z_{it} are affected significantly differently by the de-reservation compared to firms with lower Z_{it}. Our main coefficient of interest, $Post_{it} \times \hat{\theta}_i$, remains highly statistically significant and similar in magnitude.

In Columns (5) to (7), we disaggregate this effect for incumbents and entrants. Column (5) shows that, after de-reservation, the output of incumbents declined, while the output of entrants increased. Column (6) depicts our main coefficients of interest. The de-reservation policy decreased the output of incumbents with average management practices by 5.4%.

[21] It is calculated as follows: $(e^{(-0.558+0.178*3)} - 1) \times 100\%$.

Table 6: Baseline estimation results on output.

	(1) $ln(output_{it})$	(2) $ln(output_{it})$	(3) $ln(output_{it})$	(4) $ln(output_{it})$	(5) $ln(output_{it})$	(6) $ln(output_{it})$	(7) $ln(output_{it})$
$Post_{it}$	0.023*		-0.558***	-0.576***			
	(0.012)		(0.029)	(0.074)			
$\hat{\theta}_i$		0.553***					
		(0.006)					
$Post_{it} \times \hat{\theta}_i$			0.178***	0.165***			
			(0.009)	(0.006)			
Z_{it}				0.404***			0.403***
				(0.005)			(0.005)
$Post_{it} \times Z_{it}$				0.008			
				(0.008)			
$Incumbent_i \times Post_{it}$					-0.019	-0.570***	-0.508***
					(0.013)	(0.033)	(0.083)
$Entrant_i \times Post_{it}$					0.230***	-0.561***	-0.980***
					(0.032)	(0.061)	(0.166)
$Incumbent_i \times Post_{it} \times \hat{\theta}_i$						0.172***	0.159***
						(0.009)	(0.007)
$Entrant_i \times Post_{it} \times \hat{\theta}_i$						0.231***	0.218***
						(0.022)	(0.018)
$Incumbent_i \times Post_{it} \times Z_{it}$							0.000
							(0.008)
$Entrant_i \times Post_{it} \times Z_{it}$							0.050***
							(0.018)
N	234,013	190,475	190,379	178,554	234,013	190,379	178,554
R-squared	0.930	0.148	0.926	0.962	0.930	0.926	0.962
i	✓		✓	✓	✓	✓	✓
t	✓	✓	✓	✓	✓	✓	✓

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: The table reports firm-level regressions specified in equation (24). The outcome variable is the log of output. $\hat{\theta}_i$ is firm-specific rank of management practices calculated from equation (22). $Post_{it}$ is a binary indicator taking the value of one when a firm's main reserved product has been de-reserved. Z_{it} is firm-level TFP, calculated using Ackerberg et al. (2015) approach for each 2-digit industry. $Incumbent_i$ is a binary indicator taking the value of one if a firm i's main product was a reserved product before it became de-reserved. $Entrant_i$ is a binary indicator that takes the value of one if a firm i's main product was a reserved product after de-reservation, but was never produced before it became de-reserved. Columns (1) and (3) to (7) include firm and year fixed effects. Column (2) includes year fixed effects. Standard errors are clustered at the firm level.

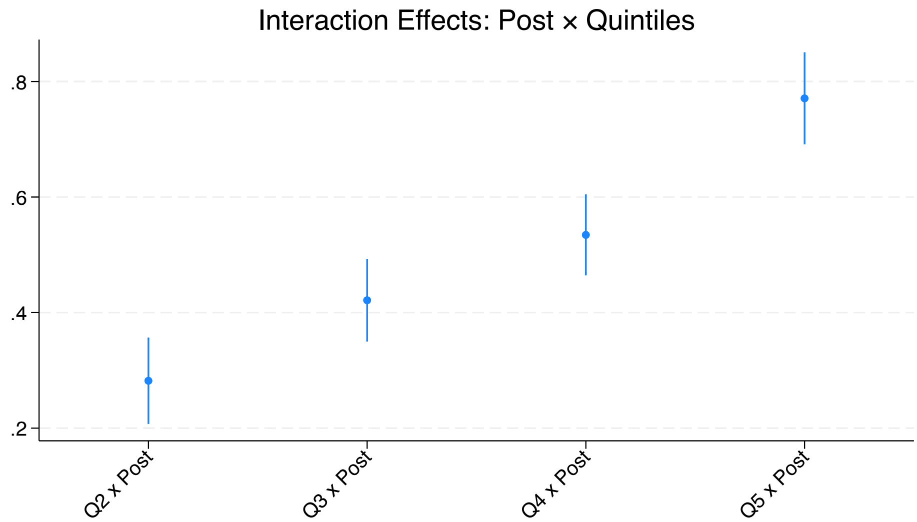
However, incumbents in the fifth quintile of $\hat{\theta}_i$ increased their output by 34%, whereas incumbents in the first quintile of $\hat{\theta}_i$ decreased their output by 33%. This is in line with proposition 1, stating that incumbents with higher $\hat{\theta}_i$ are less negatively affected by competition. Our baseline results remain unchanged after adding the interactions between Z_{it} and incumbents and entrants, in column (7), with the interaction term between Z_{it} and a de-reservation dummy being statistically zero for incumbents.[22]

Using the rank of management practices imposes a linearity assumption along different

[22]In Appendix Table B.5, we additionally control for the interaction term between post-de-reservation and log of organizational capital. Our coefficient of interest remains highly statistically significant but slightly declines in magnitude.

quintiles of $\hat{\theta}_i$. In practice, however, there may be a non-linear relationship between output and the effects of de-reservation for firms in different quintiles of management practices. To relax the linearity assumption, we create binary indicators for different quintiles of management practices instead of using the rank of management practices. By interacting these dummy variables with the $Post_{it}$ indicator, we get insights into heterogeneous effects of de-reservation along different quintiles of management practices. Point estimates plotted in Figure 7 indicate that firms in the fifth quintile of management practices are the least negatively affected by de-reservation compared to firms in the first quintile of management practices. This relationship increases in a firm's quintile of management practices. This result is in line with our findings above and demonstrates that relaxing the linearity assumption does not change our results.

Figure 7: Results on output along the quintiles of the management practices rank.



Note: The graph depicts the point estimates with 95% confidence intervals on the interaction term between $Post_{it}$ and quintile binary indicators, which are created based on the rank of management practices. The regression controls for firm and year fixed effects. Standard errors are clustered at the firm level. The first quintile serves as a reference group and is omitted.

Number of Products - We proceed by looking at changes in the number of products in Table 7. As shown in Column (1), firms affected by the de-reservation policy of their main product decreased the number of products, on average. Column (2) shows that there is no statistically significant correlation between a firm's management practices and the number of products it produces. This zero effect, together with the positive coefficient in Column (2) of Table 6, points to a larger output per product, which is in line with our theoretical model.

Our main coefficients of interest are presented in Column (3) of Table 7, showing that the de-reservation policy decreased the number of products for firms with an average $\hat{\theta}_i$ by 0.8%, on average. However, there is large heterogeneity across firms based on their management practices, with firms in the fifth quintile of $\hat{\theta}_i$ experiencing an increase of 1.2%, on average. In contrast, firms in the first quintile of management practices decreased their product scope by 2.8%. Controlling for Z_{it} in Column (4) does not alter our baseline results, with the interaction term between Z_{it} and a de-reservation dummy being statistically zero. Splitting between entrants and incumbents, Column (6) shows that incumbents, on average, decrease the number of products. However, those incumbents with higher $\hat{\theta}_i$ are less negatively affected by the policy compared to incumbents with worse management practices. This result is robust to controlling for Z_{it} with the interaction term between Z_{it} and a de-reservation dummy having a statistically zero effect. As with our output regressions in Table 6, our findings show a milder adverse effect from competition for incumbents with better management practices, which is in line with proposition 1.

Pre-trends - To check for pre-trends, we implement a recently developed methodology by Callaway and Sant'Anna (2021) that accounts for treatment effect heterogeneity in a staggered roll-out design. This method utilizes a doubly-robust DiD estimator that combines outcome-regression and inverse probability weighting to adjust for counterfactuals. We implement event-study type regressions for firms in different quintiles of management practices. Results reported in Appendix Figure A.4 show no statistically significant pre-trends, reinforcing our results.

Additionally, we follow Martin et al. (2017) and run a product-level regression, where the de-reservation dummy is regressed on lagged, first-difference changes in the product-level outcomes of interest. Having no statistically significant effect suggests that product de-reservation did not occur as a response to changes in employment, output, capital, or the number of firms. Results are presented in Appendix Table B.6.

6.2 Sector heterogeneity

As indicated in corollary 2, management practices create a heterogeneous effect of the de-reservation policy on output and the number of products only when products are

Table 7: Baseline estimation results on the number of products.

	(1) $ln(\#products_{it})$	(2) $ln(\#products_{it})$	(3) $ln(\#products_{it})$	(4) $ln(\#products_{it})$	(5) $ln(\#products_{it})$	(6) $ln(\#products_{it})$	(7) $ln(\#products_{it})$
$Post_{it}$	-0.012**		-0.038**	-0.049			
	(0.006)		(0.015)	(0.039)			
$\hat{\theta}_i$		-0.001					
		(0.002)					
$Post_{it} \times \hat{\theta}_i$			0.010**	0.009**			
			(0.004)	(0.004)			
Z_{it}				0.014***			0.013***
				(0.002)			(0.002)
$Post_{it} \times Z_{it}$				0.001			
				(0.004)			
$Incumbent_i \times Post_{it}$					-0.033***	-0.066***	-0.062
					(0.006)	(0.016)	(0.048)
$Entrant_i \times Post_{it}$					0.116***	0.088**	-0.028
					(0.016)	(0.039)	(0.087)
$Incumbent_i \times Post_{it} \times \hat{\theta}_i$						0.012***	0.012**
						(0.005)	(0.005)
$Entrant_i \times Post_{it} \times \hat{\theta}_i$						0.012	0.006
						(0.011)	(0.012)
$Incumbent_i \times Post_{it} \times Z_{it}$							-0.001
							(0.005)
$Entrant_i \times Post_{it} \times Z_{it}$							0.014*
							(0.008)
N	201734	184986	183539	172002	201734	183539	172002
R-squared	0.818	0.001	0.812	0.818	0.819	0.812	0.818
i	✓		✓	✓	✓	✓	✓
t	✓	✓	✓	✓	✓	✓	✓

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: The table reports firm-level regressions specified in equation (24). The outcome variable is the log of the number of products. $\hat{\theta}_i$ is firm-specific rank of management practices calculated from equation (22). $Post_{it}$ is a binary indicator taking the value of one when a firm's main reserved product has been de-reserved. Z_{it} is firm-level TFP, calculated using Ackerberg et al. (2015) approach for each 2-digit industry. $Incumbent_i$ is a binary indicator taking the value of one if a firm i's main product was a reserved product before it became de-reserved. $Entrant_i$ is a binary indicator that takes the value of one if a firm i's main product was a reserved product after de-reservation, but was never produced before it became de-reserved. Columns (1) and (3) to (7) include firm and year fixed effects. Column (2) includes year fixed effects. Standard errors are clustered at the firm level.

heterogeneous. Hence, if the results presented in the previous subsection are due to the mechanism exposed in our theoretical model, the effect should be larger in sectors with high product heterogeneity. To test this hypothesis, we need to first calculate the Pareto shape parameter for each of our industries, γ_s. For this, we follow Helpman et al. (2004) and Bernard et al. (2018) and rank product-level revenues within a 2-digit industry. The rank varies between 1 and 18,445. Then, for each industry, we regress the log-transformed rank variable on the log product-level revenues with year fixed effects. The coefficient from this regression is the Pareto shape parameter. Appendix Table B.7 presents the estimated Pareto shape parameter by industry.

We use our estimates for the sector's Pareto shape parameter γ_s to test this hypothesis, with higher γ_s indicating higher output dispersion across products in the sector. The regression equation is the following:

$$Y_{it} = \alpha + \beta_1 Post_{it} + \beta_2 Post_{it} \times \hat{\theta}_i + \beta_3 Post_{it} \times \gamma_s + \beta_4 Post_{it} \times \hat{\theta}_i \times \gamma_s + \eta_i + \tau_t + \varepsilon_{it}, \quad (26)$$

where Y_{it} is the log of output or the log of the number of products. The main coefficient of interest is β_4: how the heterogeneous effect of de-reservation due to management practices depends on the sector's product heterogeneity.

The results of the regressions for equation (26) are shown in Table 8. As our theory predicts, the effect of management practices is only significant in the interaction term with our measure of product heterogeneity.

Table 8: Estimation results using product differentiation measure.

	(1) $ln(output_{it})$	(2) $ln(\#products_{it})$
$Post_{it}$	0.561	0.368**
	(0.344)	(0.163)
$Post_{it} \times \hat{\theta}_i$	-0.095	-0.056
	(0.107)	(0.050)
$Post_{it} \times \gamma_s$	-3.157***	-1.146**
	(0.956)	(0.455)
$Post_{it} \times \hat{\theta}_i \times \gamma_s$	0.771**	0.187
	(0.300)	(0.141)
N	190,379	183,539
R-squared	0.926	0.812
i, t	✓	✓

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: The table reports firm-level regressions specified in equation (26). The outcome variable is log output in Column (1) and log number of products in Column (2). $\hat{\theta}_i$ is firm-specific rank of management practices calculated from equation (22). $Post_{it}$ is a binary indicator taking the value of one when a firm's main reserved product has been de-reserved. γ_s is the Pareto shape parameter, calculated as described in Section 6.2. Columns (1) and (2) include firm and year fixed effects. Standard errors are clustered at the firm level.

6.3 Robustness checks

Here, we address some potential concerns about the results presented in the last section.

A first concern relates to the construction of our *Post* variable, which is based on whether a firm's main product has been de-reserved. One might worry about the accuracy of identifying the main product at the firm level. To mitigate this concern, we change our measure of de-reservation from a firm-level variable to a sector-level variable. For this, we create a sector-level variable ($ShDeres_{st}$) that indicates the share of output de-reserved in a given sector. To avoid simultaneity problems, we set the share of output fixed to the first period in our data, specifically:

$$ShDeres_{st} = \frac{\sum_j Deres_{jt} output_{sj0}}{\sum_j output_{sj0}}, \tag{27}$$

where $Deres_{jt}$ is an indicator variable that takes the value 1 if a product has been de-reserved in period t or earlier, and $output_{sj0}$ is the output of product j in the first period of our sample. The results of the regressions with the alternative measure for de-reservation are in Table 9. Overall, they are in line with the main results presented in Tables 6 and 7.

Table 9: Robustness check using the output share of de-reserved products by industry.

	(1) ln(output)	(2) ln(# products)	(3) ln(output)	(4) ln(# products)
$ShDeres_{st}$	-0.836***	-0.053***		
	(0.038)	(0.020)		
$ShDeres_{st} \times \theta_i$	0.289***	0.016***		
	(0.012)	(0.006)		
$Incumbent_i \times ShDeres_{st}$			-0.810***	-0.088***
			(0.048)	(0.025)
$Incumbent_i \times ShDeres_{st} \times \theta_i$			0.255***	0.016**
			(0.014)	(0.007)
$Entrant_i \times ShDeres_{st}$			-0.808***	0.074
			(0.140)	(0.078)
$Entrant_i \times ShDeres_{st} \times \theta_i$			0.391***	0.017
			(0.048)	(0.022)
N	110,076	105,847	110,076	105,847
R-squared	0.923	0.832	0.923	0.832
i, t	✓	✓	✓	✓

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: The table reports firm-level regressions specified in equations (3) and (4). The outcome variable is the log of output in Column (1) and the log number of products produced by firm i at time t in Column (2). $ShDeres_{st}$ is the output share of de-reserved products in sector s at time t, calculated from equation (27). $\hat{\theta}_i$ is firm-specific rank of management practices calculated from equation (22). $Incumbent_i$ is a binary indicator taking the value of one if a firm i's main product was a reserved product before it became de-reserved. $Entrant_i$ is a binary indicator that takes the value of one if a firm i's main product was a reserved product after de-reservation, but was never produced before it became de-reserved. Columns (1) to (4) include firm and year fixed effects. Standard errors are clustered at the firm level.

Another concern relates to the accuracy of our measure of management practices.

To address this concern, we present our main results using the alternative measures of management practices as described in Section 5.2. Table 10 shows that the results using alternative MP measures remain highly robust. The coefficients in columns (3) and (4) are similar to the baseline. Appendix Table B.8 presents detailed results on output and the number of products using the days worked by managers instead of $\mathcal{O}_{it}$, $\hat{\theta}_i^{man}$, Appendix Table B.9 presents results using the value added per worker instead of Z_{it}, $\hat{\theta}_i^{Prod}$, and Appendix Table B.10 presents the results using the share of output of the smallest share to measure management practices, $\hat{\theta}_i^{min}$. Our baseline results remain robust.

Table 10: Robustness checks using alternative MP measures.

	$\hat{\theta}_i^{man}$		$\hat{\theta}_i^{prod}$		$\hat{\theta}_i^{min}$	
	(1) ln(output)	(2) ln(output)	(3) ln(output)	(4) ln(output)	(5) ln(output)	(6) ln(output)
$Post_{it}$	-0.120***		-0.546***		-0.051*	
	(0.031)		(0.029)		(0.030)	
$Post_{it} \times \hat{\theta}_i$	0.041***		0.172***		0.016*	
	(0.009)		(0.009)		(0.008)	
$Incumbent_i \times Post_{it}$		-0.192***		-0.550***		-0.083***
		(0.034)		(0.032)		(0.032)
$Incumbent_i \times Post_{it} \times \hat{\theta}_i$		0.054***		0.163***		0.017*
		(0.010)		(0.009)		(0.009)
$Entrant_i \times Post_{it}$		0.175**		-0.594***		0.072
		(0.070)		(0.063)		(0.074)
$Entrant_i \times Post_{it} \times \hat{\theta}_i$		-0.001		0.241***		0.024
		(0.021)		(0.023)		(0.021)
N	189,421	189,421	191,544	191,544	189,565	189,565
R-squared	0.920	0.921	0.926	0.926	0.925	0.925
i, t	✓	✓	✓	✓	✓	✓

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: The table reports firm-level regressions specified in equation (24). The outcome variable is the log of output. $\hat{\theta}_i^{man}$, $\hat{\theta}_i^{Prod}$, and $\hat{\theta}_i^{min}$ are firm-specific rank of management practices as described in Section 5.2. $Post_{it}$ is a binary indicator taking the value of one when a firm's main reserved product has been de-reserved. $Incumbent_i$ is a binary indicator taking the value of one if a firm i's main product was a reserved product before it became de-reserved. $Entrant_i$ is a binary indicator that takes the value of one if a firm i's main product was a reserved product after de-reservation, but was never produced before it became de-reserved. Columns (1) to (6) include firm and year fixed effects. Standard errors are clustered at the firm level.

Finally, we use a well-established, interview-based measure of management practices from the WMS constructed by Bloom et al. (2012). Results in Table 11 show that firms with better MPS experience significant increases in output after de-reservation relative to firms with poorer MPS, reinforcing our results. Again, this applies to both incumbents and entrants, with the effect being highly statistically significant for output, while the significance disappears when looking at the number of products.

Table 11: Robustness check using the MPS from Bloom et al. (2012).

	(1) ln(output)	(2) ln(output)	(3) ln(# products)	(4) ln(# products)
$Post_{it}$	-0.201**		0.018	
	(0.094)		(0.054)	
MPS_i	0.376***	0.372***	0.026***	0.028***
	(0.022)	(0.021)	(0.010)	(0.010)
$Post_{it} \times MPS_i$	0.105***		-0.012	
	(0.035)		(0.020)	
$Incumbent_i \times Post_{it}$		-0.283***		-0.000
		(0.105)		(0.065)
$Incumbent_i \times Post_{it} \times MPS_i$		0.115***		-0.012
		(0.040)		(0.025)
$Entrant_i \times Post_{it}$		-0.063		0.264***
		(0.227)		(0.097)
$Entrant_i \times Post_{it} \times MPS_i$		0.170**		-0.050
		(0.085)		(0.037)
N	97,720	97,720	86,397	86,397
R-squared	0.930	0.930	0.827	0.828
i, t	✓	✓	✓	✓

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: The table reports firm-level regressions specified in equation (24). The outcome variable is the log of output in columns (1) and (2) and the log number of products in columns (3) and (4). MPS_i is the average management practices score of firm i in sector s at time t defined from Bloom et al. (2012). $Post_{it}$ is a binary indicator taking the value of one when a firm's main reserved product has been de-reserved. $Incumbent_i$ is a binary indicator taking the value of one if a firm i's main product was a reserved product before it became de-reserved. $Entrant_i$ is a binary indicator that takes the value of one if a firm i's main product was a reserved product after de-reservation, but was never produced before it became de-reserved. Columns (1) to (4) include firm and year fixed effects. Standard errors are clustered at the firm level.

7 Welfare effects

This section aims to assess the importance of management practices and how they influence the aggregate welfare gains of industrial polices, in this case of the de-reservation policy in India. We do so in three steps. First, we parameterize the model to replicate the Indian economy using the Simulated Method of Moments (SMM). Then, we measure the aggregate effect of the de-reservation policy on welfare. Finally, we redo our simulation assuming that management practices in India are similar to the ones observed in the US.

We calibrate and simulate each industry individually, but we drop industry 30 (office equipment), as it only has around 400 observations. All other industries have at least 1,400 observations. Furthermore, we assume in the simulation that product productivities are distributed following a log-normal distribution: $z \sim Lognormal(\mu_z, \sigma_z^2)$. Hence, we solve equation (12) and the value of B_{it} numerically instead of using the closed form solution for the case where z is Pareto distributed.[23] For a detailed description of the changes to the model and the new equations for the simulation, see Appendix E.

We simulate the de-reservation policy as an exogenous entry of firms into the industry. Specifically, we measure the number of firms in industry s after de-reservation ($\hat{I}_s$) as follows:

$$\hat{I}_s = \Delta^I \phi_s I_s, \tag{28}$$

where Δ^I is the effect of de-reservation on the number of firms producing a product, ϕ_s is the share of industry output that was de-reserved between 2000 and 2008, and I_s is the original number of firms in the industry. As a measure for Δ^I, we use our result in Table 2, where we regress the de-reservation dummy on the number of firms producing a given product. This gives us $\Delta^I = 0.136$. We measure ϕ_s directly from the data, using only the market share of products in 2000, as the market shares in later years might be affected by the de-reservation. Finally, I_s is the number of firms in the industry before de-reservation.

Another effect of the de-reservation policy was to allow the entry of larger firms, as shown in Martin et al. (2017). We also show in Table 5 that new entrants are larger than incumbents in the relevant variables. To account for this, when adding new firms after de-reservation, we increase their TFP, organizational capital, and management practices distributions relative to the incumbents in their industry. Following Table 5, we increase their average TFP, organizational capital, and management practices by 2.3%, 2.1%, and 1.8%, respectively.[24]

Calibration - To calibrate our model, we first make some normalization assumptions concerning some model parameters with no direct link to the data. Specifically, we assume

[23]The reason for this change is that the log-normal distribution approximates the full distribution of firms better than the Pareto distribution, as output is too concentrated in the fat tails of the Pareto distribution (see Luttmer (2007) and Alessandria and Choi (2014)).

[24]We calculate these values as follows: $\frac{X_{entrants} - X_{incumbents}}{X_{incumbents}} \times 100$, where $X_{entrants}$ and $X_{incumbents}$ are the entrants and incumbents mean value of TFP, organizational capital, and management practices, respectively.

the range of products M_s to be 50, the overall expenditure in each sector E_s to be 100, and the mean of the product productivity distribution μ_z to be 1. Then, following the literature, we set the elasticity of substitution σ to 4.[25] Other parameters can be estimated directly from the data: the mean and standard deviation of the distribution of firm productivities (μ^s_Z, σ^s_Z), the mean and standard deviation of the distribution of organizational capital $(\mu^s_{\mathcal{O}}, \sigma^s_{\mathcal{O}})$, and the correlation between firm productivity and organizational capital $(\rho^s_{Z,\mathcal{O}})$. Table 12 shows an overview of the normalized and directly estimated parameters.

Table 12: External parameters.

Parameter	σ	M_s	E_s	I_s	μ_z	$\mu^s_{\mathcal{O}}$	$\sigma^s_{\mathcal{O}}$	μ^s_Z	σ^s_Z	$\rho^s_{Z,\mathcal{O}}$
Value	4	50 $\forall s$	100,000 $\forall s$	2000 $\forall s$	1	9.035	1.034	15.154	1.876	0.400

The values for $\mu^s_{\mathcal{O}}$, $\sigma^s_{\mathcal{O}}$, μ^s_Z, σ^s_Z, and $\rho^s_{Z,\mathcal{O}}$, are the simple average across industries. See Appendix Table F.11 for detailed information by industry.

We estimate the remaining model parameters using the SMM and the ASI data. These parameters are the mean and standard deviation of θ $(\mu^s_\theta, \sigma^s_\theta)$, the correlations between $\mathcal{O}$ and θ $(\rho^s_{\mathcal{O},\theta})$ and between Z and θ $(\rho^s_{Z,\theta})$, the fixed cost of adding a product (f^s), and the standard deviation of the product productivity distribution (σ^s_z). To estimate these parameters, we define the following expression that measures the deviation between moments in the data and in the simulation:

$$g(\xi^s) = m^s_d - m^s_v(\xi^s), \tag{29}$$

where m^s_d is a vector with moments from the data, m^s_v is the same moments measured in the simulation, and $\xi^s = (\mu^s_\theta, \sigma^s_\theta, \rho^s_{\mathcal{O},\theta}, \rho^s_{Z,\theta}, f^s, \sigma^s_z)$ is the vector of parameters to be estimated.

The optimal parameters are those that minimize the distance between the moments in the data and the moments in the simulation using a weighting matrix $\mathbf{W}$. The weighting matrix is the inverse of the estimated variance-covariance matrix of the moments in the data.[26] Specifically, we solve the following minimization problem:

$$\hat{\xi}^s = arg \ \min_{\xi^s}\{g(\xi^s)'\mathbf{W}^s g(\xi^s)\}. \tag{30}$$

[25] Broda and Weinstein (2006) find an average elasticity between products of 3.85 for the US.

[26] We estimate $\mathbf{W}^s$ by sampling 1,000 times with replacement 2,000 firms from the data. Then, we calculate the vector of moments m^s_d for each sample and calculate $\mathbf{W}^s$ as the variance-covariance matrix of the moments estimated in all the samples.

Identification - To identify the parameters in ξ^s, we choose the moments in equation (30) such that they capture the production behavior of Indian firms.

First, we use the distribution of output concentration within firms. Specifically, we calculate the firm-level standard deviation of output across products (σ_r) and compute the mean and standard deviation of this variable across firms. That is, the moments that we use are the mean and standard deviation σ_r. This captures the distribution of output concentration across firms, which is related to μ^s_θ, σ^s_θ, and σ^s_z in our model. Then, we use the correlation between the distribution of $\mathcal{O}$ and σ_r and between the distribution of Z and σ_r. These two moments are closely related to the correlation parameters $\rho^s_{\mathcal{O},\theta}$ and $\rho^s_{Z,\theta}$. Finally, we capture the distribution of the productivity threshold $\underline{z}$ by including as moments the mean and standard deviation of the log number of products across firms. These two moments closely define the fixed cost f^s and the standard deviation of the product productivity distribution σ^s_z.

Due to the randomness of the data generated, the moments and the resulting optimal parameters depend on the specific draws of the random generator. To address this issue, we repeat the SMM procedure explained above 50 times, each with a different random generator seed. We show the average value across the 50 sets of parameters.

Model fit - The fit of the moments in the simulation to their data counterparts for each industry is shown in Table 13. Overall, the model fits the data well and is capable of replicating a wide range of moments.

Table 14 shows the corresponding estimated parameter values, again for each industry. As stated above, we extract 50 different sets of parameters, and report in Table 14 only the average and the standard deviation across the 50 sets of parameters. The estimated parameters indicate that the correlation between organizational capital and management practices ($\rho^s_{\mathcal{O},\theta}$), as well as between firm productivity and management practices ($\rho^s_{Z,\theta}$), is much lower than the correlation between organizational capital and firm productivity ($\rho^s_{Z,\mathcal{O}}$). That is, while the measured value for $\rho^s_{Z,\mathcal{O}}$ in Table 12 is, on average, 0.4, the estimated values of $\rho^s_{Z,\theta}$ and $\rho^s_{\mathcal{O},\theta}$ are very close to zero, sometimes even negative. This is an indication that the assumption in our theoretical model that firm productivity and management practices are drawn from two independent distributions is likely to be fulfilled, at least for the case of India.

Table 13: Empirical and simulated moments by industry.

Ind.	Mean σ_r		Std. dev. σ_r		Corr. $\mathcal{O}$ and σ_r		Corr. Z and σ_r		Mean log(#prod.)		Std. dev. log(#prod.)	
	data	sim	data	sim	data	sim	data	sim	data	sim	data	sim
15	2.153	2.155	1.132	1.137	0.214	0.220	0.136	0.132	0.750	0.738	0.109	0.102
16	2.459	2.413	1.270	1.229	0.209	0.204	0.211	0.204	0.101	0.150	0.129	0.130
17	2.551	2.479	1.268	1.233	0.016	0.028	0.012	0.005	0.483	0.494	0.101	0.102
18	1.798	1.976	1.427	1.198	0.091	0.090	0.038	0.028	0.145	0.123	0.076	0.085
19	1.934	1.947	1.414	1.421	0.095	0.097	-0.036	-0.036	0.373	0.350	0.098	0.097
20	1.652	1.635	1.136	1.123	0.100	0.107	0.085	0.085	0.437	0.438	0.112	0.112
21	2.172	2.211	1.345	1.291	-0.003	-0.001	0.006	0.003	0.222	0.204	0.110	0.104
22	1.764	1.846	1.330	1.267	0.220	0.220	0.192	0.188	0.385	0.369	0.117	0.121
23	1.923	1.950	1.148	1.116	0.241	0.244	0.036	0.035	0.355	0.352	0.127	0.133
24	1.554	1.592	1.040	1.026	0.121	0.121	0.062	0.062	0.619	0.596	0.115	0.115
25	2.068	2.061	1.343	1.356	0.169	0.168	0.091	0.100	0.425	0.385	0.107	0.106
26	1.967	1.951	1.303	1.298	0.141	0.147	0.103	0.102	0.189	0.189	0.133	0.133
27	2.261	2.341	1.237	0.936	0.038	0.042	0.003	0.003	0.396	0.447	0.107	0.099
28	1.901	1.894	1.097	1.054	0.128	0.135	0.043	0.041	0.399	0.409	0.113	0.115
29	1.727	1.717	1.091	1.066	0.143	0.147	0.121	0.126	0.648	0.653	0.110	0.108
31	1.873	1.871	1.252	1.237	0.131	0.125	0.089	0.088	0.490	0.490	0.117	0.117
32	1.901	1.914	1.244	1.240	0.123	0.127	0.020	0.019	0.641	0.623	0.109	0.108
33	1.658	1.715	1.105	1.057	0.117	0.122	0.011	0.006	0.607	0.602	0.107	0.112
34	1.970	1.969	1.170	1.155	0.080	0.085	0.055	0.057	0.500	0.495	0.107	0.106
35	2.023	1.994	1.171	1.131	0.075	0.083	-0.052	-0.056	0.521	0.532	0.110	0.110
36	1.602	1.716	1.262	1.189	0.271	0.277	0.209	0.203	0.447	0.441	0.128	0.131

Furthermore, there are large differences across industries in the cost of adding a new product (f^s). We estimate that the higher cost of adding a product is in industries 20 (wood), 26 (other non-metallic mineral), and 28 (fabricated metal products). The lower cost is in industries 15 (food and beverages), 17 (textiles), and 25 (rubber and plastic products).

Results - We estimate the effect of different scenarios on welfare, where we estimate welfare using the utility function in equations (5) and (6). We use the expenditure shares of each industry in the ASI data to approximate the weights of each industry in the utility function, κ_s. Sector price indices P_s are endogenous and adjust in each scenario. However, we assume that the overall expenditure E is fixed and does not adjust. We calculate the change in welfare as $\Delta_U\% = (U_a - U_b)/U_b \times 100$, where U_a is the welfare in scenario a and U_b is the welfare in the benchmark simulation. The welfare values that we attribute to each industry refer to U_s in equation (6).[27] We explore five different scenarios and present the welfare effects of these scenarios in Table 15.

The first scenario, *Deres*, is the true de-reservation episode, in which we increase the number of firms in each industry following equation (28). The total increase in

[27] Note that we talk about change in industry welfare as shorthand for the change in the contribution of the industry to welfare.

Table 14: Estimated parameter values.

Ind.	μ_θ^s	σ_θ^s	$\rho_{\mathcal{O},\theta}^s$	$\rho_{Z,\theta}^s$	f^s	σ_z^s
15	0.232 (0.002)	0.043 (0.001)	0.222 (0.020)	0.139 (0.020)	2.211 (0.047)	0.178 (0.004)
16	0.205 (0.001)	0.047 (0.001)	0.211 (0.021)	0.207 (0.019)	3.773 (0.141)	0.262 (0.003)
17	0.214 (0.027)	0.044 (0.007)	0.027 (0.021)	0.007 (0.017)	2.428 (1.220)	0.245 (0.023)
18	0.239 (0.002)	0.061 (0.002)	0.094 (0.022)	0.029 (0.013)	5.320 (0.072)	0.139 (0.000)
19	0.211 (0.002)	0.085 (0.002)	0.103 (0.023)	-0.033 (0.025)	4.721 (0.068)	0.160 (0.001)
20	0.185 (0.002)	0.068 (0.002)	0.110 (0.021)	0.087 (0.017)	6.917 (0.111)	0.182 (0.002)
21	0.214 (0.031)	0.059 (0.013)	-0.002 (0.022)	0.005 (0.018)	4.535 (1.653)	0.205 (0.047)
22	0.220 (0.002)	0.073 (0.002)	0.228 (0.021)	0.195 (0.017)	4.594 (0.068)	0.147 (0.001)
23	0.203 (0.005)	0.051 (0.002)	0.243 (0.027)	0.043 (0.023)	4.955 (0.235)	0.206 (0.007)
24	0.243 (0.006)	0.092 (0.008)	0.133 (0.023)	0.071 (0.022)	3.975 (0.145)	0.102 (0.008)
25	0.242 (0.003)	0.099 (0.003)	0.182 (0.019)	0.107 (0.021)	3.331 (0.063)	0.132 (0.001)
26	0.191 (0.002)	0.064 (0.001)	0.147 (0.022)	0.106 (0.020)	5.970 (0.092)	0.212 (0.001)
27	0.209 (0.049)	0.038 (0.019)	0.040 (0.024)	0.006 (0.020)	3.780 (1.887)	0.245 (0.083)
28	0.186 (0.002)	0.054 (0.001)	0.133 (0.022)	0.045 (0.025)	5.861 (0.123)	0.231 (0.003)
29	0.187 (0.002)	0.060 (0.001)	0.145 (0.020)	0.130 (0.018)	5.145 (0.063)	0.200 (0.003)
31	0.198 (0.002)	0.063 (0.002)	0.128 (0.022)	0.090 (0.021)	4.675 (0.076)	0.191 (0.002)
32	0.221 (0.005)	0.064 (0.004)	0.131 (0.022)	0.022 (0.025)	3.345 (0.135)	0.157 (0.009)
33	0.209 (0.016)	0.059 (0.006)	0.122 (0.027)	0.011 (0.023)	4.676 (0.424)	0.165 (0.030)
34	0.210 (0.002)	0.052 (0.001)	0.083 (0.022)	0.062 (0.021)	4.181 (0.074)	0.193 (0.002)
35	0.174 (0.004)	0.058 (0.002)	0.080 (0.022)	-0.051 (0.024)	4.831 (0.182)	0.263 (0.007)
36	0.205 (0.002)	0.069 (0.003)	0.283 (0.018)	0.212 (0.017)	5.208 (0.097)	0.158 (0.003)

Standard deviation of parameters shown in parentheses.

welfare is small, of 0.29%. However, there is large heterogeneity across industries, as the de-reservation affected especially industries 18 (wearing apparel) and 19 (leather). In these two industries, the welfare gains are 3.9% and 3.46%, respectively. To put these effects into perspective, this effect is around the same order of magnitude as the 1% found by Choi and Levchenko (2025) for the effects of heavy and chemical industrial policy on short-term welfare in South Korea, Caliendo and Parro (2015) estimate an increase in Mexico's welfare from NAFTA of 1.32%, and an increase of just 0.08% in the US. Similarly, Zi (2025) estimates that trade liberalization increases China's welfare by 0.72%. Our 0.29% welfare gain is also similar to the findings in Garcia-Santana and Pijoan-Mas (2014), by which de-reservation in India lead to an increase in TFP of 0.75%.

The second scenario, θ^{US} + *Deres*, explores how management practices shape the aggregate response of welfare to de-reservation. It also utilizes the true de-reservation episode, but increases the estimated management practices to match that of the US in both the benchmark and the scenario.[28] While the welfare increase is still small (0.39%),

[28]We do so by comparing the management score measure in the World Management Survey for the US and India. Specifically, for each industry in the World Management Survey, we calculate $\Delta_{US_s} = MS_s^{US}/MS_s^{India}$, where MS refers to the management score measure in each sector-country, and then multiply the measures of θ in our simulated data by Δ_{US_s}.

it is around 36% larger than in the first scenario. Comparing the most affected industries (18 and 19) across the two scenarios shows that, had the de-reservation episode happened in an environment with better management practices, such as the US, the effect would have been 19% and 45% larger, respectively.

In the third scenario, *All Deres*, we show the welfare increase if the de-reservation affected all products in all industries. That is, we assume here that all products were reserved and then de-reserved. There are two important results from this scenario. First, the welfare effect would be much larger, 4.71%, indicating that the share of the Indian manufacturing sector affected by the de-reservation policy was relatively small. Second, there is still sector heterogeneity left even if we assume that the intensity of the de-reservation was the same across industries, with the welfare effect ranging between 4.6% and 4.9%.

The fourth scenario, θ^{Ind} *to* θ^{US}, explores the effect of an increase in management practices, independent of the de-reservation. Specifically, we increase our estimates of management practices to match those of the US, as in the second scenario, but keep the original management practices estimates in the benchmark. The effect of the increase is orders of magnitude larger than in the case of de-reservation, with an aggregated welfare increase of 82.26%. This result relates to the finding in Bloom et al. (2013) that Indian firms increased their productivity by 17% after one year of managerial training. Our results indicate that the (welfare) gains could be even larger if management practices were increased to the US level. We interpret this as an indication that policies targeting an improvement in management practices might be more important than policies targeting market liberalization, such as the de-reservation policy in India. Note, however, that both policies might go hand-in-hand, as one of the effects of the de-reservation policy in India was also to open the market to firms with better management practices.

Finally, the fifth scenario, θ^{Ind} *to* θ^{US} *+ Deres*, adds the de-reservation episode to the previous scenario. As expected, the total welfare effects change only slightly, from 82.26% to 82.79%, and are similar to adding the welfare effects from the second and the fourth scenarios.

Table 15: Simulation results.

Ind	(1) **Deres**	(2) θ^{US} **+ Deres**	(3) **All Deres**	(4) θ^{Ind} **to** θ^{US}	(5) θ^{Ind} **to** θ^{US} **+ Deres**
15	0.481	0.576	4.712	57.773	58.565
16	0.000	0.000	4.710	173.656	173.656
17	0.064	0.120	4.713	157.013	157.183
18	3.900	4.660	4.660	28.349	33.990
19	3.461	5.033	4.705	44.829	50.758
20	0.274	0.488	4.790	64.729	65.267
21	0.352	0.539	4.857	111.887	112.747
22	0.059	0.083	4.716	36.594	36.690
23	0.000	0.000	4.688	86.409	86.409
24	0.200	0.245	4.603	16.462	16.744
25	0.624	0.778	4.688	27.811	28.731
26	0.251	0.362	4.730	85.127	85.692
27	0.158	0.292	4.716	162.041	162.509
28	0.459	0.680	4.768	101.715	102.866
29	0.302	0.501	4.768	82.541	83.209
31	0.191	0.284	4.746	69.000	69.383
32	0.033	0.042	4.688	42.372	42.425
33	0.146	0.219	4.700	53.948	54.199
34	0.000	0.000	4.796	73.522	73.522
35	0.410	0.751	4.894	186.317	187.725
36	0.467	0.657	4.717	43.175	43.949
Total	0.289	0.394	4.707	82.260	82.795

The benchmark in column (2) already uses the management practices of the US. All values are in percentage changes.

8 Conclusion

This paper highlights the critical role of management practices in shaping firm responses to industrial policy, particularly in a developing economy such as India. Using a theoretical model and India's de-reservation policy as a quasi-natural experiment, this paper shows that firms with better management practices are less adversely affected by an industrial policy that fosters market entry and competition. This effect is explained by these firms being specialized in fewer and more productive products, which makes them less vulnerable to changes in competition. Our findings underscore the importance of management practices in determining the effects of industrial policy on firm output and product scope.

Our simulation results show a 0.29% increase in welfare from the de-reservation policy. The same policy in an environment with better management practices would have increased welfare by 0.39%. Increasing our estimate of management practices to match those in the

US, we estimate an 82.26% welfare gain, which is orders of magnitude larger than in the case of de-reservation. We interpret it as evidence that policies targeting the improvement of management practices might be more important to improve aggregate welfare than industrial policies targeting market entry and competition. This result reinforces the findings by Bloom et al. (2013), who showed that providing training to managers has increased the productivity of Indian firms by 17% after one year.

Our paper has important implications for policymakers. One way to boost firms' management practices would be to provide free public managerial training programs on basic operations such as quality control and inventory. Additionally, a competitive incentive package from the board of directors could also improve managerial performance. Another way to encourage managerial learning could be by establishing mobility programs between managers of firms in developed and developing countries. Further research is needed to identify which of the potential policies for improving managerial practices are the most optimal in increasing welfare in developing countries, taking into account the unique features of each country, such as the level of human capital, institutional development, and the distance from the technological frontier.

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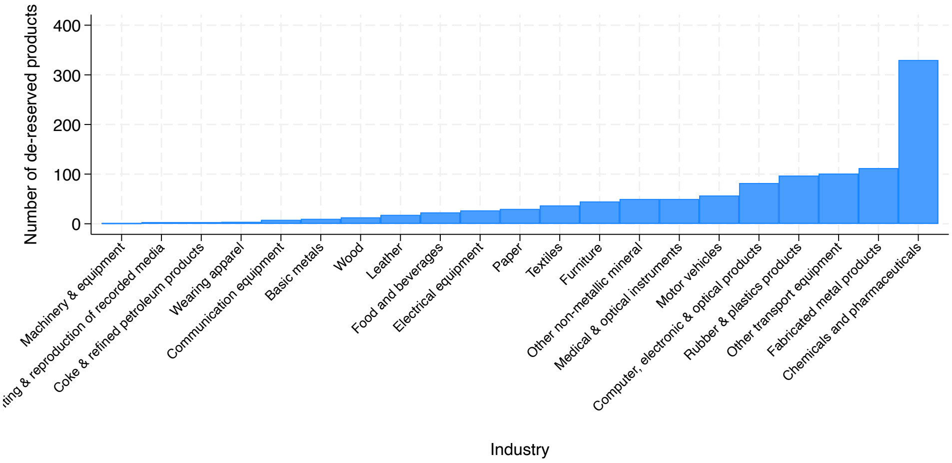
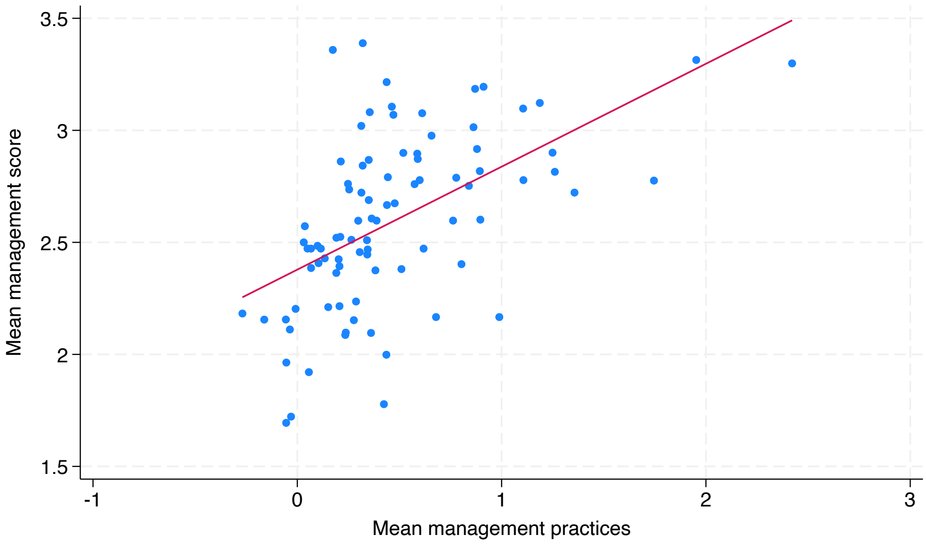
A Figures

Figure A.1: Number of de-reserved products by industry.



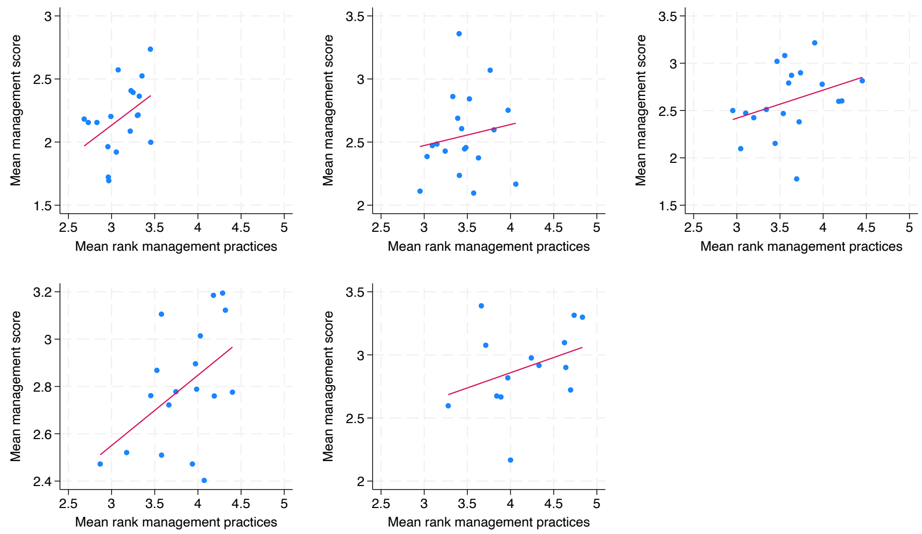
Note: Data on the number of de-reserved products from 1997 to 2015 is taken from Martin et al. (2017).

Figure A.2: Correlation between management score and measured management practices.



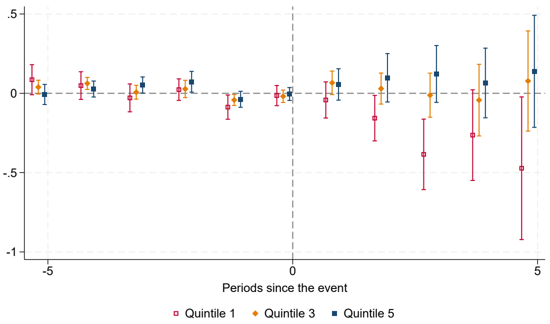
Note: Correlation graph between the average management score and management practices measured as a residual of equation (22). Management score data is taken from the World Management Survey constructed by Bloom et al. (2012). Bins are 2-digit industry and employment categories for (i) 50-100, (ii) 101-250, (iii) 251-500, (iv) 501-1000, and (v) 1000+ employees.

Figure A.3: Correlation between management score and rank of management practices for each employment category.

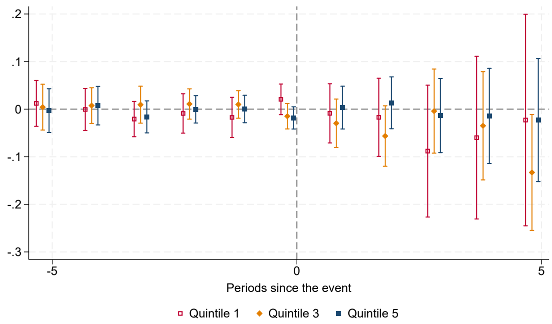


Note: Correlation graph between the average management score and the rank of management practices for each employment category. Management score data is taken from the World Management Survey constructed by Bloom et al. (2012). Bins are 2-digit industry and employment categories for (i) 50-100, (ii) 101-250, (iii) 251-500, (iv) 501-1000, and (v) 1000+ employees.

Figure A.4: Event study using Callaway and Sant'Anna (2021) by quintiles of management practices.



(a) ln(Output)



(b) ln(# products)

Note: The graph depicts the point estimates with 95% confidence intervals of de-reservation on log output in Panel (a) and log number of products in Panel (b) by quintiles of management practices. Callaway and Sant'Anna (2021) estimator is applied using inverse probability weighting difference-in-differences estimator with stabilized weights. The regression controls for firm and year fixed effects.

B Tables

Table B.1: Stylized facts at the product-level controlling for time trend.

	(1) $Added_{ijt}$	(2) $Added_{ijt}$	(3) $Added_{ijt}$	(4) $Added_{ijt}$	(5) $Added_{ijt}$	(6) $Added_{ijt}$
$Post_{it}$	-0.015**	0.010	0.000			
	(0.007)	(0.007)	(.)			
Time relative to de-reservation	-0.001	0.002	0.007***	-0.001	0.001	0.005**
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
$Post_{it} \times reserved_j$		-0.075***	-0.075***			
		(0.011)	(0.014)			
$Incumbent_i \times Post_{it}$				-0.026***	0.005	0.000
				(0.007)	(0.008)	(.)
$Entrant_i \times Post_{it}$				0.072***	0.061***	0.000
				(0.016)	(0.017)	(.)
$Incumbent_i \times Post_{it} \times reserved_j$					-0.082***	-0.083***
					(0.011)	(0.015)
$Entrant_i \times Post_{it} \times reserved_j$					0.040**	0.026
					(0.016)	(0.019)
N	186,089	186,089	147,782	186,089	186,089	147,782
R-squared	0.402	0.402	0.517	0.421	0.422	0.517
i	✓	✓		✓	✓	
j	✓	✓	✓	✓	✓	✓
t	✓	✓	✓	✓		
$i \times t$			✓			✓

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: The table reports product-level regressions specified in equation (1). The outcome variable is a binary indicator taking the value of one when the product j is added by firm i at time t. $Post_{it}$ is a binary indicator taking the value of one when a firm's main reserved product has been de-reserved. Time relative to de-reservation is an event time trend that equals the year of de-reservation minus the current year and is always 0 for establishments that never produced de-reserved products. $Incumbent_i$ is a binary indicator taking the value of one if a firm i's main product was a reserved product before it became de-reserved. $Entrant_i$ is a binary indicator that takes the value of one if a firm i's main product was a reserved product after de-reservation, but was never produced before it became de-reserved. $Reserved_j$ is a dummy indicator for whether or not the product j is reserved. Columns (1), (2), (4), and (5) include firm, product, and year fixed effects. Columns (3) and (6) include product, firm-year fixed effects. Standard errors are clustered at the firm level.

B.1 Pre-trends test

To test for no pre-trends, we follow Martin et al. (2017) and run a product-level regression, where a de-reservation dummy is regressed on lagged, first-difference changes in the product-level outcomes of interest. Having no statistically significant effect suggests that product de-reservation did not occur as a response to changes in employment, output, capital or the number of firms. Since some products are not observed every year, we calculate the lagged first difference by taking the outcome in the previous period observed

Table B.2: Number of firms at the product-level using logarithmic transformation.

	(1) $\#Firms_{jt}$	(2) $\#IncumbentFirms_{jt}$	(3) $\#EntrantFirms_{jt}$
$Post_{jt}$	0.137**	-0.747***	3.651***
	(0.055)	(0.159)	(0.560)
N	29,540	18,884	5,765
R-squared	0.009	0.067	0.182
j, t	✓	✓	✓

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: The table reports product-level regressions of the number of firms producing a given product on the de-reservation indicator. The outcome variables are transformed using the logarithmic transformation. $\#IncumbentFirms_{jt}$ is the number of firms that produce a given product before it was de-reserved. $\#EntrantFirms_{jt}$ is the number of firms producing a given product after it was de-reserved. $Post_{jt}$ is a binary indicator taking the value of one when a product j is de-reserved at time t. Standard errors are clustered at the product level.

Table B.3: Stylized facts at the firm-level controlling for time trend.

	(1) ln(output)	(2) ln(# products)	(3) ln(output)	(4) ln(# products)
$Post_{it}$	0.028**	-0.013**		
	(0.013)	(0.006)		
Time relative to de-reservation	-0.002	0.000	-0.004	0.000
	(0.003)	(0.001)	(0.003)	(0.001)
$Incumbent_i \times Post_{it}$			-0.008	-0.034***
			(0.013)	(0.006)
$Entrant_i \times Post_{it}$			0.241***	0.114***
			(0.033)	(0.016)
N	234,013	201,734	234,013	201,734
R-squared	0.930	0.818	0.930	0.819
i, t	✓	✓	✓	✓

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: The table reports firm-level regressions specified in equations (3) and (4). The outcome variable is the log number of products produced by firm i at time t, and the log of output. $Post_{it}$ is a binary indicator taking the value of one when a firm's main reserved product has been de-reserved. Time relative to de-reservation is an event time trend that equals the year of de-reservation minus the current year and is always 0 for establishments that never produced de-reserved products. $Incumbent_i$ is a binary indicator taking the value of one if a firm i's main product was a reserved product before it became de-reserved. $Entrant_i$ is a binary indicator that takes the value of one if a firm i's main product was a reserved product after de-reservation, but was never produced before it became de-reserved. Columns (1) to (4) include firm and year fixed effects. Standard errors are clustered at the firm level.

minus the outcome in the prior period observed and dividing by the gap. For de-reserved products, the sample is limited to years up to the de-reservation year in order to not include the effects of de-reservation. All regressions include product and year fixed effects.

Table B.4: Estimation results of de-reservation on changes in organizational capital.

	(1) $\Delta\mathcal{O}_{it}$	(2) $\Delta\mathcal{O}_{it}$
$Post_{it}$	0.000	
	(0.000)	
Incumbent $\times Post_{it}$		0.000
		(0.000)
Entrant $\times Post_{it}$		0.001
		(0.001)
N	70,982	70,982
R-squared	0.371	0.371
i, t	✓	✓

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: The table reports firm-level regressions of changes in organizational capital on de-reservation. The outcome variable is the first difference of log organizational capital as calculated in equation (17). $Post_{it}$ is a binary indicator taking the value of one when a firm's main reserved product has been de-reserved. $Incumbent_i$ is a binary indicator taking the value of one if a firm i's main product was a reserved product before it became de-reserved. $Entrant_i$ is a binary indicator that takes the value of one if a firm i's main product was a reserved product after de-reservation, but was never produced before it became de-reserved. Columns (1) and (2) include firm and year fixed effects. Standard errors are clustered at the firm level.

Table B.6 shows that the coefficients are close to 0 and are statistically insignificant, suggesting that there are no significant pre-trends.

Table B.5: Robustness check controlling for Organizational Capital.

	(1) ln(output)	(2) ln(output)	(3) ln(output)	(4) ln(output)	(5) ln(output)	(6) ln(output)	(7) ln(output)
$Post_{it}$	0.023* (0.012)		-0.558*** (0.029)	-0.464*** (0.102)			
$\hat{\theta}_i$		0.553*** (0.006)					
$Post_{it} \times \hat{\theta}_i$			0.178*** (0.009)	0.095*** (0.008)			
Z_{it}				0.360*** (0.006)			0.361*** (0.006)
$Post_{it} \times Z_{it}$				0.007 (0.009)			
$\mathcal{O}_{it}$				1.313*** (0.379)			1.299*** (0.376)
$Post_{it} \times \mathcal{O}_{it}$				0.009** (0.004)			
$Incumbent_i \times Post_{it}$					-0.019 (0.013)	-0.570*** (0.033)	-0.495*** (0.111)
$Entrant_i \times Post_{it}$					0.230*** (0.032)	-0.561*** (0.061)	0.317 (0.302)
$Incumbent_i \times Post_{it} \times \hat{\theta}_i$						0.172*** (0.009)	0.091*** (0.008)
$Entrant_i \times Post_{it} \times \hat{\theta}_i$						0.231*** (0.022)	0.135*** (0.025)
$Incumbent_i \times Post_{it} \times Z_{it}$							0.000 (0.010)
$Entrant_i \times Post_{it} \times Z_{it}$							0.022 (0.026)
$Incumbent_i \times Post_{it} \times \mathcal{O}_{it}$							0.015*** (0.004)
$Entrant_i \times Post_{it} \times \mathcal{O}_{it}$							-0.050** (0.019)
N	234,013	190,475	190,379	102,101	234,013	190,379	102,101
R-squared	0.930	0.148	0.926	0.968	0.930	0.926	0.968
i	✓		✓	✓	✓	✓	✓
t	✓	✓	✓	✓	✓	✓	✓

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: The table reports firm-level regressions specified in equation (24). The outcome variable is the log of output. $\hat{\theta}_i$ is firm-specific rank of management practices calculated from equation (22). $Post_{it}$ is a binary indicator taking the value of one when a firm's main reserved product has been de-reserved. Z_{it} is firm-level TFP, calculated using Ackerberg et al. (2015) approach for each 2-digit industry. $\mathcal{O}_{it}$ is log of organizational capital calculated as stated in section 5.1. $Incumbent_i$ is a binary indicator taking the value of one if a firm i's main product was a reserved product before it became de-reserved. $Entrant_i$ is a binary indicator that takes the value of one if a firm i's main product was a reserved product after de-reservation, but was never produced before it became de-reserved. Columns (1) to (7) include firm and year fixed effects. Standard errors are clustered at the firm level.

Table B.6: Pre-trends test at the product level.

	(1)	(2)	(3)	(4)
	$Post_{it}$	$Post_{it}$	$Post_{it}$	$Post_{it}$
Lag $\Delta Labor_{it}$	0.001			
	(0.001)			
Lag $\Delta Output_{it}$		-0.000		
		(0.001)		
Lag $\Delta Capital_{it}$			0.000	
			(0.001)	
Lag $\Delta Firms_{it}$				0.001
				(0.002)
N	20,870	20,870	20,851	20,937
R-squared	0.019	0.019	0.019	0.019

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: The table reports product-level regressions of de-reservation on lagged first difference changes in labor, output, capital, and number of firms. Since some products are not observed every year, the lagged first difference is calculated by taking the outcome in the previous period observed minus the outcome in the prior period observed and dividing by the gap. The lagged first differences are observed starting from 2002. For de-reserved products, the sample is limited to years before the de-reservation year. Regressions are weighted by initial labor shares. Standard errors are clustered at the product level.

Table B.7: Industry estimates of the Pareto shape parameter

Industry	**Pareto shape parameter**
15	0.3277
16	0.2996
17	0.3427
18	0.4401
19	0.3851
20	0.3999
21	0.3610
22	0.3693
23	0.2672
24	0.3491
25	0.3561
26	0.3496
27	0.3376
28	0.3635
29	0.3536
30	0.3077
31	0.3353
32	0.3206
33	0.3600
34	0.3290
35	0.3277
36	0.3062

Table B.8: Baseline estimation results. Alternative MP estimation using manager days worked.

	(1) ln(output)	(2) ln(output)	(3) ln(output)	(4) ln(output)	(5) ln(# products)	(6) ln(# products)	(7) ln(# products)	(8) ln(# products)
$Post_{it}$	-0.120***	-0.245***			-0.041***	-0.059		
	(0.031)	(0.075)			(0.015)	(0.039)		
$Post_{it} \times \hat{\theta}_i^{man}$	0.041***	0.051***			0.009**	0.009*		
	(0.009)	(0.007)			(0.004)	(0.005)		
Z_{it}		0.409***		0.409***		0.014***		0.013***
		(0.005)		(0.005)		(0.002)		(0.002)
$Post_{it} \times Z_{it}$		0.013*				0.001		
		(0.008)				(0.004)		
$Incumbent_i \times Post_{it}$			-0.192***	-0.177**			-0.065***	-0.077
			(0.034)	(0.082)			(0.016)	(0.048)
$Incumbent_i \times Post_{it} \times \hat{\theta}_i^{man}$			0.054***	0.063***			0.009*	0.011**
			(0.010)	(0.007)			(0.005)	(0.005)
$Entrant_i \times Post_{it}$			0.175**	-0.331*			0.085**	-0.004
			(0.070)	(0.170)			(0.039)	(0.086)
$Entrant_i \times Post_{it} \times \hat{\theta}_i^{man}$			-0.001	0.006			0.012	0.008
			(0.021)	(0.017)			(0.011)	(0.012)
$Incumbenti \times Post_{it} \times Z_{it}$				-0.002				0.000
				(0.008)				(0.005)
$Entrant_i \times Post_{it} \times Z_{it}$				0.051***				0.010
				(0.018)				(0.008)
N	189,421	173,563	189,421	173,563	180,942	165,514	180,942	165,514
R-squared	0.920	0.961	0.921	0.961	0.813	0.819	0.814	0.820
i, t	✓	✓	✓	✓	✓	✓	✓	✓

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: The table reports firm-level regressions specified in equation (24). The outcome variable is the log of output. $\hat{\theta}_i^{man}$ is the firm-specific rank of management practices using days worked by managers instead of $\mathcal{O}_{it}$ in equation (22). $Post_{it}$ is a binary indicator taking the value of one when a firm's main reserved product has been de-reserved. Z_{it} is firm-level TFP, calculated using Ackerberg et al. (2015) approach for each 2-digit industry. $Incumbent_i$ is a binary indicator taking the value of one if a firm i's main product was a reserved product before it became de-reserved. $Entrant_i$ is a binary indicator that takes the value of one if a firm i's main product was a reserved product after de-reservation, but was never produced before it became de-reserved. Columns (1) to (8) include firm and year fixed effects. Standard errors are clustered at the firm level.

Table B.9: Baseline estimation results. Alternative MP estimation using value added per worker.

	(1) ln(output)	(2) ln(output)	(3) ln(output)	(4) ln(output)	(5) ln(# products)	(6) ln(# products)	(7) ln(# products)	(8) ln(# products)
$Post_{it}$	-0.546***	-0.922***			-0.039**	-0.089**		
	(0.029)	(0.094)			(0.015)	(0.043)		
$Post_{it} \times \hat{\theta}_i^{prod}$	0.172***	0.169***			0.010**	0.009**		
	(0.009)	(0.007)			(0.004)	(0.004)		
$Prod_{it}$		0.337***		0.337***		0.011***		0.011***
		(0.005)		(0.005)		(0.002)		(0.002)
$Post_{it} \times Prod_{it}$		0.035***				0.004		
		(0.008)				(0.004)		
$Incumbent_i \times Post_{it}$			-0.550***	-1.305***			-0.071***	-0.070
			(0.032)	(0.106)			(0.017)	(0.054)
$Incumbent_i \times Post_{it} \times \hat{\theta}_i^{prod}$			0.163***	0.160***			0.013***	0.013***
			(0.009)	(0.007)			(0.005)	(0.005)
$Entrant_i \times Post_{it}$			-0.594***	-0.847***			0.093**	-0.053
			(0.063)	(0.226)			(0.039)	(0.100)
$Entrant_i \times Post_{it} \times \hat{\theta}_i^{prod}$			0.241***	0.241***			0.010	0.004
			(0.023)	(0.019)			(0.011)	(0.012)
$Incumbent_i \times Post_{it} \times Prod_{it}$				0.069***				-0.000
				(0.009)				(0.005)
$Entrant_i \times Post_{it} \times Prod_{it}$				0.021				0.013
				(0.019)				(0.008)
N	191,544	180,513	191,544	180,513	184,563	173,590	184,563	173,590
R-squared	0.926	0.958	0.926	0.958	0.812	0.818	0.812	0.818
i, t	✓	✓	✓	✓	✓	✓	✓	✓

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: The table reports firm-level regressions specified in equation (24). The outcome variable is the log of output. $\hat{\theta}_i^{Prod}$ is the firm-specific rank of management practices using value added per worker instead of Z_{it} in equation (22). $Post_{it}$ is a binary indicator taking the value of one when a firm's main reserved product has been de-reserved. $Prod_{it}$ is value added per worker. $Incumbent_i$ is a binary indicator taking the value of one if a firm i's main product was a reserved product before it became de-reserved. $Entrant_i$ is a binary indicator that takes the value of one if a firm i's main product was a reserved product after de-reservation, but was never produced before it became de-reserved. Columns (1) to (8) include firm and year fixed effects. Standard errors are clustered at the firm level.

Table B.10: Baseline estimation results. Alternative MP estimation using the output share of the smallest product.

	(1) ln(output)	(2) ln(output)	(3) ln(output)	(4) ln(output)	(5) ln(# products)	(6) ln(# products)	(7) ln(# products)	(8) ln(# products)
$Post_{it}$	-0.051*	-0.095			-0.108***	-0.154***		
	(0.030)	(0.076)			(0.014)	(0.038)		
$Post_{it} \times \hat{\theta}_i^{min}$	0.016*	0.017**			0.031***	0.038***		
	(0.008)	(0.007)			(0.004)	(0.004)		
Z_{it}		0.405***		0.404***		0.014***		0.014***
		(0.005)		(0.005)		(0.002)		(0.002)
$Post_{it} \times Z_{it}$		0.006				0.002		
		(0.008)				(0.004)		
$Incumbent_i \times Post_{it}$			-0.083***	-0.046			-0.108***	-0.134***
			(0.032)	(0.087)			(0.015)	(0.048)
$Incumbent_i \times Post_{it} \times \hat{\theta}_i^{min}$			0.017*	0.019***			0.024***	0.030***
			(0.009)	(0.007)			(0.005)	(0.005)
$Entrant_i \times Post_{it}$			0.072	-0.362**			-0.109***	-0.278***
			(0.074)	(0.171)			(0.037)	(0.077)
$Entrant_i \times Post_{it} \times \hat{\theta}_i^{min}$			0.024	0.014			0.070***	0.079***
			(0.021)	(0.017)			(0.011)	(0.011)
$Incumbent_i \times Post_{it} \times Z_{it}$				-0.002				0.000
				(0.009)				(0.005)
$Entrant_i \times Post_{it} \times Z_{it}$				0.050***				0.014*
				(0.018)				(0.008)
N	189,565	177,823	189,565	177,823	182,779	171,328	182,779	171,328
R-squared	0.925	0.962	0.925	0.962	0.812	0.818	0.812	0.818
i, t	✓	✓	✓	✓	✓	✓	✓	✓

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: The table reports firm-level regressions specified in equation (24). The outcome variables are the log of output and the log number of products. $\hat{\theta}_i^{min}$ is the firm-specific rank of management practices calculated using equation (23) instead of equation (22). $Post_{it}$ is a binary indicator taking the value of one when a firm's main reserved product has been de-reserved. $Prod_{it}$ is value added per worker. $Incumbent_i$ is a binary indicator taking the value of one if a firm i's main product was a reserved product before it became de-reserved. $Entrant_i$ is a binary indicator that takes the value of one if a firm i's main product was a reserved product after de-reservation, but was never produced before it became de-reserved. Columns (1) to (8) include firm and year fixed effects. Standard errors are clustered at the firm level.

C Theory

Derivation of equation (13) - Start from the maximization problem in (12), together with the constraint in equation (8):

$$
\begin{aligned}
\mathcal{L} &= \int_{j\in\Omega_{is}} \pi_{isjt} - f dj + \lambda\left(\mathcal{O}_i - \int_{j\in\Omega_{is}} o_{isjt} dj\right)\\
\frac{\partial \mathcal{L}}{\partial o_{isjt}} &= \theta_i(\sigma-1)E_{st}P_{st}^{\sigma-1}Z_{it}^{\sigma-1}z_{isj}^{\sigma-1}o_{isjt}^{\theta_i(\sigma-1)-1} - \lambda \overset{!}{=} 0\\
o_{isjt} &= \left(\frac{z_{isj}}{z_{isj'}}\right)^{\frac{\sigma-1}{1-\theta_i(\sigma-1)}} o_{isj'}\\
\mathcal{O}_i &= \int_{j\in\Omega_{is}} o_{isjt} dj = \int_{j\in\Omega_{is}} \left(\frac{z_{isj}}{z_{isj'}}\right)^{\frac{\sigma-1}{1-\theta_i(\sigma-1)}} o_{isj'} dj\\
&= z_{isj}^{-\frac{\sigma-1}{1-\theta_i(\sigma-1)}} o_{isjt} \int_{j\in\Omega_{is}} z_{isj}^{\frac{\sigma-1}{1-\theta_i(\sigma-1)}} dj\\
o_{isjt} &= \frac{\mathcal{O}_i}{\int_{j\in\Omega_{is}} z_{isj}^{\frac{\sigma-1}{1-\theta_i(\sigma-1)}} dj} z_{isj}^{\frac{\sigma-1}{1-\theta_i(\sigma-1)}},
\end{aligned}
$$

where j and j' denote different products.

Derivation of equation (15) - Start with the profit per product, after substituting in the optimal o_{isjt} is:

$$
\pi_{isjt} = z_{isj}^{\frac{\sigma-1}{1-\theta_i(\sigma-1)}} E_{st}P_{st}^{\sigma-1}Z_{it}^{\sigma-1}\left(\frac{\mathcal{O}_i}{B_{it}}\right)^{\theta_i(\sigma-1)}. \tag{31}
$$

Use the Pareto distribution to integrate over products in B_{it} and Π_{it}:

$$
\begin{aligned}
B_{it} &= M_s \int_{z_{ist}}^{\infty} z_{isj}^{\frac{\sigma-1}{1-\theta_i(\sigma-1)}} f(z)dz\\
&= M_s \frac{\gamma_s z_{ist}^{\frac{\sigma-1}{1-\theta_i(\sigma-1)}-\gamma_s}}{\gamma_s - \frac{\sigma-1}{1-\theta_i(\sigma-1)}}\\
\Pi_{it} &= \int_{j\in\Omega_{is}} z_{isj}^{\frac{\sigma-1}{1-\theta_i(\sigma-1)}} E_{st}P_{st}^{\sigma-1}Z_{it}^{\sigma-1}\left(\frac{\mathcal{O}_i}{B_{it}}\right)^{\theta_i(\sigma-1)} - f dj\\
&= E_{st}P_{st}^{\sigma-1}Z_{it}^{\sigma-1}\mathcal{O}_i^{\theta_i(\sigma-1)}B_{it}^{1-\theta_i(\sigma-1)} - (1-F(z_{ist}))M_s f\\
&= E_{st}P_{st}^{\sigma-1}Z_{it}^{\sigma-1}\mathcal{O}_i^{\theta_i(\sigma-1)}\left(\frac{\gamma_s M_s}{\gamma_s - \frac{\sigma-1}{1-\theta_i(\sigma-1)}}\right)^{1-\theta_i(\sigma-1)} z_{ist}^{(\sigma-1)(1+\gamma_s\theta_i)-\gamma_s} - f M_s z_{ist}^{-\gamma_s},
\end{aligned} \tag{32}
$$

where M_s is the number of products produced in sector s, i.e. $M_s = |\Omega_s|$ and we used equation (13) and the definition of B_{it} to rewrite the overall profit.

Finally, the FOC of the maximization problem in (14):

$$\begin{aligned}
\frac{\partial \Pi_{it}}{\partial z_{ist}} &= ((\sigma-1)(1+\gamma_s\theta_i)-\gamma_s)E_{st}P_{st}^{\sigma-1}Z_{it}^{\sigma-1}\mathcal{O}_i^{\theta_i(\sigma-1)}\left(\gamma_{1is}M_s\right)^{1-\theta_i(\sigma-1)} z_{ist}^{(\sigma-1)(1+\gamma_s\theta_i)-\gamma_s-1} \\
&\quad + \gamma_s f M_s z_{ist}^{-\gamma_s-1} \overset{!}{=} 0 \\
z_{ist}^{(\sigma-1)(1+\gamma_s\theta_i)} &= \frac{\gamma_{1is} f M_s}{(1-\theta_i(\sigma-1))E_{st}P_{st}^{\sigma-1}Z_{it}^{\sigma-1}\mathcal{O}_i^{\theta_i(\sigma-1)}\left(\gamma_{1is}M_s\right)^{1-\theta_i(\sigma-1)}} \\
z_{ist} &= \left[\frac{\left(\gamma_{1is}M_s\right)^{\theta_i(\sigma-1)} f}{(1-\theta_i(\sigma-1))E_{st}P_{st}^{\sigma-1}Z_{it}^{\sigma-1}\mathcal{O}_i^{\theta_i(\sigma-1)}}\right]^{\frac{1}{(\sigma-1)(1+\gamma_s\theta_i)}},
\end{aligned}$$

where $\gamma_{1is} = \frac{\gamma_s}{\gamma_s - \frac{\sigma-1}{1-\theta_i(\sigma-1)}}$

Derivation of equation (16) - Starting from firm profit:

$$\begin{aligned}
\Pi_{it} &= E_{st}P_{st}^{\sigma-1}Z_{it}^{\sigma-1}\mathcal{O}_i^{\theta_i(\sigma-1)}\left(\gamma_{1is}M_s\right)^{1-\theta_i(\sigma-1)} z_{ist}^{(\sigma-1)(1+\gamma_s\theta_i)-\gamma_s} - fM_s z_{ist}^{-\gamma_s} \\
&= E_{st}P_{st}^{\sigma-1}Z_{it}^{\sigma-1}\left(\gamma_{1is}M_s\right)^{1-\theta_i(\sigma-1)}\left[\frac{\left(\gamma_{1is}M_s\right)^{\theta_i(\sigma-1)} f}{(1-\theta_i(\sigma-1))E_{st}P_{st}^{\sigma-1}Z_{it}^{\sigma-1}}\right]^{1-\frac{\gamma_s}{(\sigma-1)(1+\gamma_s\theta_i)}} \mathcal{O}_i^{\frac{\gamma_s\theta_i}{1+\gamma_s\theta_i}} \\
&- fM_s\left[\frac{\left(\gamma_{1is}M_s\right)^{\theta_i(\sigma-1)} f}{(1-\theta_i(\sigma-1))E_{st}P_{st}^{\sigma-1}Z_{it}^{\sigma-1}}\right]^{-\frac{\gamma_s}{(\sigma-1)(1+\gamma_s\theta_i)}} \mathcal{O}_i^{\frac{\gamma_s\theta_i}{1+\gamma_s\theta_i}} \\
&= \left(E_{st}^{\frac{1}{\sigma-1}} Z_{it}P_{st}\right)^{\frac{\gamma_s}{1+\gamma_s\theta_i}} f^{1-\frac{\gamma_s}{(\sigma-1)(1+\gamma_s\theta_i)}} M_s^{\frac{1}{1+\gamma_s\theta_i}} \mathcal{O}_i^{\frac{\gamma_s\theta_i}{1+\gamma_s\theta_i}} \\
&\times \left[\frac{\left(\gamma_{1is}\right)^{\theta_i(\sigma-1)}}{(1-\theta_i(\sigma-1))}\right]^{-\frac{\gamma_s}{(\sigma-1)(1+\gamma_s\theta_i)}} \left(\frac{\gamma_{1is}}{(1-\theta_i(\sigma-1))}-1\right) \\
&= X_{1ist}\mathcal{O}_i^{\frac{\gamma_s\theta_i}{1+\gamma_s\theta_i}},
\end{aligned}$$

where $X_{1ist} = \left(E_{st}^{\frac{1}{\sigma-1}} Z_{it}P_{st}\right)^{\frac{\gamma_s}{1+\gamma_s\theta_i}} f^{1-\frac{\gamma_s}{(\sigma-1)(1+\gamma_s\theta_i)}} M_s^{\frac{1}{1+\gamma_s\theta_i}} \left[\frac{(\gamma_{1is})^{\theta_i(\sigma-1)}}{(1-\theta_i(\sigma-1))}\right]^{-\frac{\gamma_s}{(\sigma-1)(1+\gamma_s\theta_i)}} \left(\frac{\gamma_{1is}}{(1-\theta_i(\sigma-1))}-1\right)$.

D Proofs

It is useful to express B_{it} in terms of model parameters and the organizational capital using the optimal productivity threshold from equation (15):

$$B_{it} = M_s\gamma_{1is}\left[\frac{(\gamma_{1is}M_s)^{\theta_i(\sigma-1)}f}{(1-\theta_i(\sigma-1))E_{st}P_{st}^{\sigma-1}Z_{it}^{\sigma-1}\mathcal{O}_i^{\theta_i(\sigma-1)}}\right]^{\frac{1}{(\sigma-1)(1+\gamma_s\theta_i)}\left(\frac{\sigma-1}{1-\theta_i(\sigma-1)}-\gamma_s\right)}$$

$$= (M_s\gamma_{1is})^{\frac{1}{(1-\theta_i(\sigma-1))(1+\gamma_s\theta_i)}}\left[\frac{f}{(1-\theta_i(\sigma-1))E_{st}P_{st}^{\sigma-1}Z_{it}^{\sigma-1}\mathcal{O}_i^{\theta_i(\sigma-1)}}\right]^{\frac{(\sigma-1)(1+\gamma_s\theta_i)-\gamma_s}{(1-\theta_i(\sigma-1))(\sigma-1)(1+\gamma_s\theta_i)}}.$$

Denote the total revenues of a firm by R_{it}:

$$R_{it} = M_s\int_{z_{ist}}^{\infty} r_{isjt}f(z)dz = M_s\int_{z_{ist}}^{\infty} p_{isjt}q_{isjt}f(z)dz$$

$$= \sigma E_{st}P_{st}^{\sigma-1}Z_{it}^{\sigma-1}\mathcal{O}_i^{\theta_i(\sigma-1)}B_{it}^{1-\theta_i(\sigma-1)}$$

$$= \sigma E_{st}^{\frac{\gamma_s}{(\sigma-1)(1+\gamma_s\theta_i)}}P_{st}^{\frac{\gamma_s}{1+\gamma_s\theta_i}}Z_{it}^{\frac{\gamma_s}{1+\gamma_s\theta_i}}\mathcal{O}_i^{\frac{\gamma_s\theta_i}{1+\gamma_s\theta_i}}(M_s\gamma_{1is})^{\frac{1}{1+\gamma_s\theta_i}}\left[\frac{f}{(1-\theta_i(\sigma-1))}\right]^{\frac{(\sigma-1)(1+\gamma_s\theta_i)-\gamma_s}{(\sigma-1)(1+\gamma_s\theta_i)}}.$$

Proof Proposition 1 - Start from total revenues, denoted by R_{it}:

$$R_{it} = \sigma E_{st}^{\frac{\gamma_s}{(\sigma-1)(1+\gamma_s\theta_i)}}P_{st}^{\frac{\gamma_s}{1+\gamma_s\theta_i}}Z_{it}^{\frac{\gamma_s}{1+\gamma_s\theta_i}}\mathcal{O}_i^{\frac{\gamma_s\theta_i}{1+\gamma_s\theta_i}}(M_s\gamma_{1is})^{\frac{1}{1+\gamma_s\theta_i}}\left[\frac{f}{(1-\theta_i(\sigma-1))}\right]^{\frac{(\sigma-1)(1+\gamma_s\theta_i)-\gamma_s}{(\sigma-1)(1+\gamma_s\theta_i)}}.$$

The elasticity with respect to P_j:

$$\frac{\partial R_{it}}{\partial P_{st}}\frac{P_{st}}{R_{it}} = \frac{\gamma_s}{1+\theta_i\gamma_s},$$

which is positive. That is, as firms face stronger competition in a sector (P_{st} decreases), they decrease their revenues. Furthermore, note that, when $\theta_i = 0$ the elasticity is γ_s.

Now, take the derivative of the elasticity with respect to the management practices:

$$\frac{\partial\left|\frac{\partial R_{it}}{\partial P_r}\frac{P_r}{R_{it}}\right|}{\partial\theta_i} = -\frac{\gamma_s^2}{(1+\theta_i\gamma_s)^2}, \quad (33)$$

which is negative.

For the second part of proposition 1, the elasticity of the number of products ($N_{ist} =$

$(1 - F(\underline{z}_{ist}))M_s)$ with respect to a change in the price index P_{st}:

$$\frac{\partial N_{ist}}{\partial P_{st}}\frac{P_{st}}{N_{ist}} = -\gamma_s \underline{z}_{ist}^{-\gamma_s-1} M_s \frac{\partial \underline{z}_{ist}}{\partial P_{st}} \frac{P_{st}}{\underline{z}_{ist}^{-\gamma_s} M_s} = -\gamma_s \frac{\partial \underline{z}_{ist}}{\partial P_{st}} \frac{P_{st}}{\underline{z}_{ist}} = \frac{\gamma_s}{1+\theta_i\gamma_s},$$

which is positive. That is, as incumbent firms face stronger competition in a sector (P_{st} decreases), they decrease the number of products they produce, dropping their less productive products (i.e., increasing their productivity threshold), and concentrating their organizational capital on their more productive products. Again, when $\theta_i = 0$ the elasticity is γ_s.

Finally, taking the derivative of the elasticity with respect to the management practices:

$$\frac{\partial \left| \frac{\partial N_{ist}}{\partial P_r} \frac{P_r}{N_{ist}} \right|}{\partial \theta_i} = -\frac{\gamma_s^2}{(1+\theta_i\gamma_s)^2}, \tag{34}$$

which is negative. Firms with better management practices react less to changes in the price index.

Proof Lemma 1 - Start from total revenues, denoted by R_{it}:

$$R_{it} = \sigma E_{st}^{\frac{\gamma_s}{(\sigma-1)(1+\gamma_s\theta_i)}} P_{st}^{\frac{\gamma_s}{1+\gamma_s\theta_i}} Z_{it}^{\frac{\gamma_s}{1+\gamma_s\theta_i}} \mathcal{O}_i^{\frac{\gamma_s\theta_i}{1+\gamma_s\theta_i}} (M_s\gamma_{1is})^{\frac{1}{1+\gamma_s\theta_i}} \left[\frac{f}{(1-\theta_i(\sigma-1))}\right]^{\frac{(\sigma-1)(1+\gamma_s\theta_i)-\gamma_s}{(\sigma-1)(1+\gamma_s\theta_i)}}.$$

The elasticity with respect to Z_{it}:

$$\frac{\partial R_{it}}{\partial Z_{it}}\frac{Z_{it}}{R_{it}} = \frac{\gamma_s}{1+\theta_i\gamma_s},$$

which is positive. That is, as the number of products available for production increases, their revenues increase.

Taking the derivative of the elasticity with respect to the management practices:

$$\frac{\partial \left| \frac{\partial R_{it}}{\partial Z_{it}} \frac{Z_{it}}{R_{it}} \right|}{\partial \theta_i} = -\frac{\gamma_s^2}{(1+\theta_i\gamma_s)^2}, \tag{35}$$

which is negative.

For the increase in the number of products for entrants, we look at the elasticity of the number of products ($N_{ist} = (1 - F(\underline{z}_{ist}))M_s$) with respect to a change in the number of products M_s:

$$\frac{\partial N_{ist}}{\partial Z_{it}}\frac{Z_{it}}{N_{ist}} = -\gamma_s z_{ist}^{-\gamma_s-1} M_s \frac{\partial z_{ist}}{\partial Z_{it}}\frac{Z_{it}}{z_{ist}^{-\gamma_s} M_s} = -\gamma_s \frac{\partial z_{ist}}{\partial P_{st}}\frac{P_{st}}{z_{ist}} = \frac{\gamma_s}{1+\theta_i\gamma_s},$$

which is positive. Hence, firms increase the number of products following de-reservation.

Taking the derivative of the elasticity with respect to the management practices:

$$\frac{\partial \left|\frac{\partial N_{ist}}{\partial Z_{it}}\frac{Z_{it}}{N_{ist}}\right|}{\partial\theta_i} = -\frac{\gamma_s^2}{(1+\theta_i\gamma_s)^2}, \tag{36}$$

which is negative.

E Simulation

We use in the simulation a version of the model in which the product-level productivity draws, $G(z)$, are distributed log-normal instead of a Pareto distribution as in the theoretical model. Here we show the more general version of the model we use in the simulation, where the integral over z is solved numerically.

Consumer's utility and aggregated demand are unchanged:

$$\begin{aligned} U_t &= \sum_s \kappa_s \log U_{st} \\ U_{st} &= \left(\int_{i\in\Lambda_s}\int_{j\in\Omega_{is}} q_{isjt}^{\frac{\sigma-1}{\sigma}}\, dj di\right)^{\frac{\sigma}{\sigma-1}} \\ q_{isjt} &= \kappa_s E_t P_{st}^{\sigma-1} p_{isjt}^{-\sigma}. \end{aligned}$$

The profit from producing a product j and the maximization problem are unchanged:

$$\begin{aligned} \pi_{isjt} &= E_{st} P_{st}^{\sigma-1} Z_{it}^{\sigma-1} z_{isj}^{\sigma-1} o_{isjt}^{\theta_i(\sigma-1)} \\ \Pi_{ist} &= \arg\max_{\{z_{ist}\}}\; E_{st} P_{st}^{\sigma-1} Z_{it}^{\sigma-1} \mathcal{O}_i^{\theta_i(\sigma-1)} B_{it}^{1-\theta_i(\sigma-1)} - f(1-F(z_{ist}))M_s. \end{aligned}$$

The optimal threshold is identified by solving:

$$\begin{aligned}
\frac{\partial \Pi_{ist}}{\partial \underline{z}_{ist}} &= -E_{st}P_{st}^{\sigma-1}Z_{it}^{\sigma-1}\left(\frac{\mathcal{O}_i}{B_{it}}\right)^{\theta_i(\sigma-1)}(1-\theta_i(\sigma-1))M_s \underline{z}_{ist}^{\frac{\sigma-1}{1-\theta_i(\sigma-1)}} f(\underline{z}_{ist}) + fM_s f(\underline{z}_{ist}) \stackrel{!}{=} 0 \\
0 &= f - (1-\theta_i(\sigma-1))E_{st}P_{st}^{\sigma-1}Z_{it}^{\sigma-1}\left(\frac{\mathcal{O}_i}{B_{it}}\right)^{\theta_i(\sigma-1)} \underline{z}_{ist}^{\frac{\sigma-1}{1-\theta_i(\sigma-1)}}.
\end{aligned}$$

We find the optimal $\underline{z}_{ist}$ by finding the root of the equation above, solving $B_{it} = M_s \int_{\underline{z}_{ist}}^{\infty} z_{isj}^{\frac{\sigma-1}{1-\theta_i(\sigma-1)}} f(z)dz$ numerically.

With the optimal $\underline{z}_{ist}$ and the corresponding B_{it}, we can solve for product-level prices, firm-level revenues, and firm-level number of products:

$$\begin{aligned}
p_{ijt} &= \frac{\sigma}{\sigma-1} Z_{it}^{-1} z_{isj}^{-\frac{1}{1-\theta_i(\sigma-1)}} \left(\frac{\mathcal{O}_i}{B_{it}}\right)^{-\theta_i} \\
R_{it} &= \sigma E_{st} P_{st}^{\sigma-1} Z_{it}^{\sigma-1} \mathcal{O}_i^{\theta_i(\sigma-1)} B_{it}^{1-\theta_i(\sigma-1)} \\
N_{it} &= (1-F(\underline{z}_{ist}))M_s.
\end{aligned}$$

We compute P_{st} and iterate over P_{st} and B_{it} until convergence.

$$\begin{aligned}
P_{st} &= \left(\int_{i\in\Lambda_s}\int_{j\in\Omega_{is}} p_{isjt}^{1-\sigma} dj di\right)^{\frac{1}{1-\sigma}} \\
&= \left(\int_{i\in\Lambda_s} M_s \int_{\underline{z}_{ist}}^{\infty} p_{isjt}^{1-\sigma} f(z) dj di\right)^{\frac{1}{1-\sigma}} \\
&= \left(\int_{i\in\Lambda_s} M_s \int_{\underline{z}_{ist}}^{\infty} \left(\frac{\sigma}{\sigma-1} Z_{it}^{-1} z_{isj}^{-\frac{1}{1-\theta_i(\sigma-1)}} \left(\frac{\mathcal{O}_i}{B_{it}}\right)^{-\theta_i}\right)^{1-\sigma} f(z) dj di\right)^{\frac{1}{1-\sigma}} \\
&= \left(\int_{i\in\Lambda_s} \left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma} Z_{it}^{\sigma-1} \left(\frac{\mathcal{O}_i}{B_{it}}\right)^{\theta_i(\sigma-1)} M_s \int_{\underline{z}_{ist}}^{\infty} z_{isj}^{\frac{\sigma-1}{1-\theta_i(\sigma-1)}} f(z) dj di\right)^{\frac{1}{1-\sigma}} \\
&= \left(\int_{i\in\Lambda_s} \left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma} Z_{it}^{\sigma-1} \mathcal{O}_i^{\theta_i(\sigma-1)} B_{it}^{1-\theta_i(\sigma-1)} di\right)^{\frac{1}{1-\sigma}}.
\end{aligned}$$

To compute the standard deviation of products within firms, we use the output of a product, which is given by:

$$
\begin{aligned}
r_{isjt} = p_{isjt}q_{isjt} = \kappa_s E_t P_{st}^{\sigma-1} p_{isjt}^{1-\sigma} &= \kappa_s E_t P_{st}^{\sigma-1} \left(\frac{\sigma}{\sigma-1} \frac{1}{Z_{it} z_{isj} o_{isjt}^{\theta_i}} \right)^{1-\sigma} \\
&= \kappa_s E_t P_{st}^{\sigma-1} \left(\frac{\sigma}{\sigma-1} \frac{1}{Z_{it}} \right)^{1-\sigma} \left(\frac{\mathcal{O}_i}{B_{it}} \right)^{\theta_i(\sigma-1)} z_{isj}^{\frac{\sigma-1}{1-\theta_i(\sigma-1)}} \\
&= X_{ist} z_{isj}^{\frac{\sigma-1}{1-\theta_i(\sigma-1)}},
\end{aligned}
$$

where $X_{ist} = \kappa_s E_t P_{st}^{\sigma-1} \left(\frac{\sigma}{\sigma-1} \frac{1}{Z_{it}} \right)^{1-\sigma} \left(\frac{\mathcal{O}_i}{B_{it}} \right)^{\theta_i(\sigma-1)}$.

Take logs and assuming $\log X_{ist}$ and $\log z_{isj}$ are independent:

$$
\begin{aligned}
\log r_{isjt} &= \log X_{ist} + \frac{\sigma-1}{1-\theta_i(\sigma-1)} \log z_{isj} \\
Var(\log r_{isj}) &= \left(\frac{\sigma-1}{1-\theta_i(\sigma-1)} \right)^2 Var(\log z_{isj}) \\
SD(\log r_{isj}) &= \frac{\sigma-1}{(1-\theta_i(\sigma-1))} SD(\log z_{isj}).
\end{aligned}
$$

F Parameterization

Table F.11: External parameters by industry

Ind	μ_Z^s	σ_Z^s	μ_{OC}^s	σ_{OC}^s	$\rho_{Z,OC}^s$
15	9.056	1.106	14.931	2.059	0.545
16	12.251	1.415	14.314	2.000	0.747
17	8.681	0.927	15.705	1.751	0.378
18	10.329	0.931	16.105	1.305	0.188
19	8.860	0.802	15.377	1.634	0.120
20	10.503	1.024	13.448	1.794	0.635
21	9.071	0.918	14.792	1.807	0.600
22	11.543	1.312	15.018	1.966	0.696
23	8.096	1.232	15.197	1.956	0.424
24	9.739	1.223	15.569	1.979	0.612
25	7.906	0.881	15.132	1.853	0.299
26	9.736	1.094	13.762	2.312	0.733
27	7.847	0.932	15.253	1.865	0.380
28	7.336	0.888	14.938	1.959	0.067
29	8.995	0.917	15.269	1.935	0.542
31	8.729	1.010	15.412	1.942	0.433
32	7.713	1.056	16.145	1.788	-0.022
33	7.368	1.007	15.493	1.715	0.131
34	7.352	0.862	16.008	1.888	0.319
35	7.824	0.863	15.393	1.907	-0.011
36	10.799	1.306	14.970	1.989	0.594