Bottlenecks versus ripple effects:
The role of linkages in India's product market liberalization*

Vybhavi Balasundharam†

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Abstract

I investigate the impact of input-output linkages on aggregate productivity gains from reducing distortions in a market. Removing distortionary policies that implicitly tax larger and more productive firms within a market propagates to upstream suppliers as a demand shock and to downstream customers as an input cost shock. I analyze the heterogeneous response of firms in these linked markets, leveraging the elimination of firm-size restrictions for a set of product markets in India during the 2000s combined with rich firm-level data. Upon reform, I find an increase in aggregate productivity from both the directly exposed and linked markets. These gains are primarily driven by reallocation of inputs to larger and more productive firms. However, productivity gains are attenuated when linked markets are highly concentrated. More productive firms in concentrated linked markets raise their markups in response to the demand or supply shock, thereby increasing misallocation. The adjustment of markups is consistent with models where demand elasticity decreases with firm productivity and underlines the substantial bias from ignoring market structure in linked markets when assessing the impact of piecemeal reforms. Conditional on the supply-chain being sufficiently competitive, linkages can amplify the overall gains from reforms that reduce distortions in a market.

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†Ph.D. Job Market Candidate, Department of Economics, University of Michigan. For more information, vybhavi@umich.edu and vybhavi.com

1 Introduction

Misallocation of inputs from high- to low-productivity firms and industries has been identified as an important driver of productivity losses in developing countries (Hsieh and Klenow, 2009). Sources of such misallocations include domestic policies, institutions and market frictions that implicitly subsidize smaller and less productive firms[1]. Most markets in developing countries suffer from some form of this distortion. The question then arises as to how reducing distortions in one market affects misallocation in linked upstream supplier and downstream customer markets. On the one hand, correcting for distortions in one small market can potentially have large spillover effects that result in improved allocation across the supply-chain. On the other hand, a second-best world offers no assurance of efficiency gains from selective interventions in one sector if uncorrectable market failures are present in linked markets. My paper examines how market power and the resulting markup distortions in linked markets produces different gains in response to a regulatory regime change. Specifically, I focus on the interaction of two deviations from an efficient economy: imperfect competition and regulations that restrict firm-size, both creating production bottlenecks in the supply-chain. In other words, this paper addresses two related questions: How do IO linkages amplify or attenuate the gains from reducing distortions within one market and what role does market power play in this transmission?

I leverage the removal of a policy that restricted firm size in a set of product markets in India as a quasi-natural experiment to shed light into the propagation of distortions through IO linkages. This *reservation* of products for exclusive manufacturing by Small-scale industries (SSI) in India (i.e., establishments with plant and machinery value less than Rs. 10 million) is an example of a regulation that distorts the size-distribution of firms[2]. The main advantage of this setting is that the policy affected only around 20 percent of all products and a quarter of the establishments in India, leaving a large subset of firms to serve as control group as well as to identify the effects on linked markets. A growing literature finds such regulations reduce aggregate productivity by restricting the growth of productive

[1] Examples of market imperfections that are costly for large firms include poor quality of the managerial delegation environment (Akcigit et al., 2016), frictions in financial markets (Midrigan and Xu, 2014; Gopinath et al., 2017), rent-seeking and unequal regulation enforcement (Almeida et al., 2011), markup dispersion (Peters, 2013)

[2] Such size distortionary policies are popular across the world including product market regulations that restrict size in the Japanese retail sector (Lewis, 2004), labor regulations that are only applicable for large firms in many countries (Garicano et al., 2016), financial subsidies for Small and Medium Enterprises (SMEs) in Korea and India (Rotemberg, 2017). Even a regulation that applies uniformly to all firms within a market may generate misallocation. For example, tariffs applied to narrowly defined categories of goods will differentially affect importing firms relative to ones that source domestically. Martin et al. (2017), Tewari and Wilde (2018), Galle (2018) are other papers that use the Indian reservation episode to quantify the costs of size-distortionary policies on affected markets.

firms (Restuccia and Rogerson, 2008; Guner et al., 2008). In addition, they fail to protect employment, deter investment and technology upgrades (Bertrand and Kramarz, 2002). Consistent with studies on the effects of such distortions, Indian reservation episode resulted in sub-optimal firm-size with substantial output and productivity loss in the reserved markets (Garcia-Santana and Pijoan-Mas, 2014). While removing distortions within these markets enhances its productivity, such improvements do not occur without large reallocations and displacements of inputs. From a policy perspective, it is therefore important to evaluate the incidence of productivity gains across the supply-chain. The goal of this paper is to provide such an evaluation.

My analysis of the ramifications of India's removal of reservation proceeds as follows. First, I estimate the effect of size distortionary polices on misallocation and productivity in directly affected markets. I do so by comparing the evolution of reserved and non-reserved product markets before and after the liberalization. The plausibly exogenous variation generated by the liberalization offers new evidence on the predominant role of misallocation in driving productivity using relatively weak assumptions. Second, I evaluate the spillovers of this intervention, tracing how the deregulation propagates through the supply-chain. I disentangle the effects on directly linked markets exploiting the availability of detailed product-firm-level data on prices and quantities. I compare markets by the strength of their linkages to the reserved markets. Using a structural model of production, I isolate the markup component of product price from marginal costs and estimate heterogenous responses by firm productivity and market concentration. This firm-level evidence captures reallocation gains from supply/demand shocks that extend beyond output growth and price changes and addresses mitigating role of market power. Finally, I estimate the size of the multiplier effect on aggregate productivity growth from linked markets. I also decompose the productivity growth into within-firm productivity gains, improved allocation in the market and the efficiency loss from increasing market concentration to understand the mechanisms through which reducing distortionary policies operate.

To guide the empirical analysis, I present a framework where production is organized in a vertical supply-chain setting with three markets: upstream, reserved and downstream. Each market has a finite number of heterogeneous firms with endogenous markups. Firms in the reserved market also face an output distortion that limits their size. When this distortive policy is eliminated, output increases and prices decrease as production is shifted from smaller, less productive firms to larger, more productive firms who were previously constrained by the policy.[3] These changes in prices and output propagate via the supply-

[3]The reallocation from removing size distortions is driven by both an increase in the expected value of entry leading to a larger mass of firms in the economy (Bento and Restuccia, 2017) and the expansion of the

chain through two channels. First, distorted firms purchase less-than-optimal amounts of inputs, thereby depressing the sales of these upstream suppliers.[4] When this distortion is removed, factor demand increases leading to higher output and potentially higher prices in imperfectly competitive upstream markets. If the upstream firms respond heterogeneously, the resulting reallocation would amplify the productivity gains if inputs are shifted to more productive firms. The resulting price changes could also have feedback effects as the marginal costs of reserved firms change. Second, the fall in prices reduces the marginal costs of downstream customers that use the reserved product as an input in production. By reallocating inputs to more productive firms, reforms in linked markets may have a cascading effect that reduces misallocation in downstream markets as well. When downstream markets are perfectly competitive, these customers completely pass-through the cost reductions. However, imperfect competition could mitigate the reallocation gains when markup dispersion increases from incomplete pass-through. Thus, the overall gains from removing a regulatory bottleneck is theoretically ambiguous, and consequently requires an empirical exploration.

Using firm-level panel data from the Annual Survey of Industries, I show that eliminating size restrictions significantly increases output and decreases prices within the reserved markets. This policy change induces a positive demand shock for upstream suppliers and lowers input costs for downstream customers. In both the linked markets, output growth is driven by larger and more productive firms when the markets are competitive. However, in concentrated markets, more productive firms raise their markups in response to the demand/supply shock, resulting in a substantial increase in aggregate markups and dispersion. Consequently, as market concentration increases, output growth is driven be relatively less productive firms in these linked markets. The increase in aggregate markups also abates output growth in concentrated downstream markets. These results are consistent with a large class of models where more productive firms face lower demand elasticities and charge higher markups.[5]

Aggregating the nationally representative firm-level data to the product-level, I quantify the aggregate productivity implications of these firm-level responses and the resulting redistribution. Within reserved markets, the intervention led to productivity growth of 18% with 82% of this growth driven by reallocation of inputs to more productive firms and the remaining from within-firm productivity growth. Hence, reallocation stressed in heterogeneous firm models plays a dominant role here, relative to the channels stressed in homogenous firm theories (such as better incentives to adopt new technologies). Productivity increased by

most efficient firms, which in equilibrium improves the selection of producers in the market (Bartelsman et al., 2013)

[4]Downstream production bottlenecks acts like taxes on upstream firms' final output as identified by Jones (2011a,b). It reduces the value the firm receives from producing a given level of output.

[5]See Atkeson and Burstein (2008), Melitz and Ottaviano (2008) and Dhingra and Morrow (2015).

an average of 5% in upstream and -0.5% in downstream markets. These gains diminish with increasing market concentration as inputs are reallocated to initially low-markup, less productive firms. In addition, market-power induced distortions have feedback effects by reducing the productivity gains within markets that were directly affected by the reform. In total, this reform increased productivity of the manufacturing sector by 2.3% without accounting for linkages. With a competitive supply-chain, the growth in aggregate productivity is augmented by directly linked markets with an estimated multiplier effect of around 1.6 (i.e. productivity increases by 3.7%). However, these multiplier effects fully dissipate when linked markets are highly concentrated.[6] The empirical estimates in this paper suggest that the cascading effects of improved allocation dominates the efficiency loss from imperfect competition only when the supply-chain is sufficiently competitive.

Therefore, the overall gains from correcting for distortions in one market depends on the underlying market structure of the linked markets. Industrial policies that open up particular product markets can exacerbate the efficiency loss in linked industries by increasing the average markups and dispersion[7]. This paper is one of the first to explore this allocative efficiency channel in an industrial policy context, specifically focusing on transmission through demand and supply shocks induced by eliminating size distortionary policies. Given that many developing countries adopt industrial policies that direct resources towards selected sectors, it is critical to account for the vertical linkages when deciding which sectors to promote. The findings here emphasize the need to account for market-power induced inefficiencies in determining the overall gains from industrial-policy interventions. My results suggest that removing distortionary policies in parts of a sufficiently competitive production network can trigger reallocation of resources across producers in the supply-chain and lead to large overall gains in the economy.

The paper contributes to several strands of literature. First, the paper is related to the large body of macro-development literature on the misallocation of resources. This research finds that microeconomic distortions that induce misallocation of resources across firms and sectors are an important source of cross-country productivity differences (e.g., Banerjee and Duflo, 2005; Hsieh and Klenow, 2009; Restuccia and Rogerson, 2008; Midrigan and Xu, 2014). My paper draws on this literature but shifts the focus to the spillover effects of distortions that affect particular markets and highlights the role of market power in this transmission. IO linkages are an important channel to explore because industrial development process requires the growth of entire distribution of suppliers and downstream producers, not just

[6]Back-of-the-envelope calculations estimate a downstream HHI of 3390 and upstream HHI of 7500 to eliminate all gains. This concentration is at least at the 90th percentile of the sample.

[7]See Dhingra and Morrow (2015), Arkolakis et. al (2015), Edmond et al. (2015, 2018) and Holmes et al. (2014) for welfare implications of variable markups.

particular firms or product markets (Hirschman, 1958).[8] Even a regulation that is applied to all markets within the supply-chain may generate more misallocation within some relative to others, thereby creating bottlenecks.

My paper builds on the burgeoning literature that studies the transmission of distortions through IO linkages[9]. In related work, Liu (2018) looks at production networks under market imperfections where these distortions accumulate through backward demand linkages, thereby generating aggregate sales distortions that are largest in the most upstream markets. Recent work by Grassi (2017) studies the dampening effects of competition on transmission of idiosyncratic productivity shocks, while Baquee (2018) presents a framework where deviations from perfect competition affects the amplification of shocks by generating firm entry and exit across the network. In contrast, this paper empirically evaluates the role of market power in mitigating the inter-industry propagation of efficiency gains from alleviating a prevalent policy distortion. To the best of my knowledge, this is also the first paper to study both the upstream and downstream effects of market failures utilizing a unique natural experiment that translates nicely to available firm balance sheet data and produces more direct empirical estimates. The setup is rich enough to test the impact on firm-level distribution and its aggregate productivity implications within directly and indirectly exposed markets. This provides a deeper understanding of how these frictions propagate and impact other firms, an aspect missing from the existing literature that uses aggregated IO tables to mainly estimate the role of firm-specific or sector-specific shocks in generating aggregate fluctuations.

An important contribution of my paper is to connect the above literature on propagation of distortions through IO linkages to the recent literature that explicitly models the welfare implications of variable markups (see Footnote 7). In these models, a policy is welfare improving when inputs are allocated to firms with higher markups. Hence, markups are not only costly because they act like a uniform output tax, but the resulting markup dispersion misallocates factors of production. There are relatively few papers in the empirical literature that have tested the theoretical predictions of this class of models, and my paper addresses this gap[10]. My empirical evidence of increased misallocation in concentrated markets that

[8]Modeling firms' behavior along a vertical channel has important implications for the analysis of price dynamics in the economy as a whole (Chevalier, Kashyap and Rossi, 2003) and for the passthrough effects of both foreign-trade policy (Amiti and Konings, 2007) and industrial policy (Lane, 2017).

[9]Key theoretical references include Basu and Fernald (2002), Acemoglu et al. (2012), Jones (2013), Bartelme and Gorodnichenko (2015), Baqaee (2017a), Caliendo et al. (2018)

[10]Weinberg (2017) is the closest to my paper. He finds sectors using imported inputs become more misallocated relative to exporting sectors that face more competition from exchange rate appreciations in Chile. However, he does not find any significant effects from tariff changes, a policy distortion. Moreover, as emphasized by Restuccia and Rogerson (2013), changes in misallocation measured at business cycle frequency or exchange rate fluctuations need to be treated with extreme caution as these measures can be heavily driven by adjustment costs, and not a true measure of misallocation.

face demand/supply shocks using disaggregated firm-level data provide empirical support for these class of models.

Finally, there has been renewed interest in studying firm market power, due to several secular trends such as increasing concentration and long- run rise in average markups (see DeLoecker and Eeckhout (2017)). Barkai (2017) and Autor et al. (2017) explain the secular declines in labor share from the increase in sector-level and firm-level concentration. Gilbukh and Roldan (2018) attribute the increase in dispersion at the top of the markup distribution to the decline in business dynamism. In this paper, I document increasing markup dispersion from deregulation in related markets. My paper also relates to the pass-through literature. De loecker et al. (2016) focuses on incomplete pass through of input tariff shocks that reduce the welfare gains (of lower prices and higher average productivity) from import competition in the output sectors. Relatedly, Amiti et al. (2012) find that the most productive firms import the most and also have the lowest pass-through. I find evidence of heterogeneous pass-through that lower the gains from industrial policy interventions.

The remainder of the paper proceeds as follows. Section 2 provides background on the Small-Scale Industry Reservation in India. In Section 3, I set up a stylized framework in a supply chain setting with heterogeneous firms and endogenous markups to provide intuition on how the removal of distortions propagate through IO linkages and its aggregate productivity implications. Section 4 describes the data, the construction of the exposure measures, and proceeds to present the identification strategy with tests of the main identifying assumptions. Section 5 analyzes the impact of the Indian reform across the firm distribution and surveys different theoretical mechanisms through which these patterns can be realized. Section 6 discusses the effects on aggregate productivity and provides empirical estimates. Section 7 concludes.

2 Background on the Small Scale Reservation in India

The reservation and de-reservation of products for exclusive manufacturing by small firms has several features that allow me to explore the transmission of policy distortions through IO linkages.

The small-scale industry (SSI) in India contributes almost 40 percent to gross industrial value-added and is the second largest employer after agriculture. The development of SSI has been an economic priority because of its potential to generate employment and a more equitable distribution of income. Promotion measures included subsidies for credit, energy and capital, technical assistance and excise tax exemption. With the aim of protecting SSI from competition and fostering labor-intensive growth, India implemented a policy of reservation of certain products for exclusive manufacturing by SSI firms in 1967, i.e. only firms with historic plant and machinery value of less than Rs. 10 million were permitted to operate in these product markets[11][12]. The number of reserved products had grown from 47 products to over 1000 products in 1996. Production of these reserved items accounted for about 13 percent of total manufacturing output in India in 1989 (Mohan, 2002). The choice of products to be reserved and the timing of dereservation was itself reportedly arbitrary according to the policy notes (Hussain 1997; Mohan 2002). The only criterion was the ability of SSI to manufacture such items. Hence, the number of reserved products and the timing of removal varied greatly across industries. Figure 1 shows the trends of dereservation episodes as well the variation of reservation across industries.

The timing of the elimination of these reservations alleviates concerns of other large-scale economic reforms around the time driving the effects. India began economic liberalization in the 1990s following an economic crisis in 1991 and this included the widely studied episodes of delicensing and trade liberalization. One of the last remnants of the protectionist era was this reservation. Growing concerns about SSI's ability to compete with imported goods and produce high-quality goods that meet growing consumer demands nudged the dismantling of this policy[13]. Beginning in 1997, the products were dereserved in a staggered manner with the pace accelerating to around 253 products dereserved at the end of 2007 and the final set of 20 products being dereserved in 2015. My analysis using this regulatory reform leverages a difference-in-difference strategy. This methodology requires that there are no differences in trends of outcome variables of interest between the control and treatment groups prior to the reform (i.e. parallel trend assumption). Existing literature studying these dereservation episodes in other contexts lends confidence on the plausible exogeneity of the reform itself. Martin et al. (2017) and Tewari and Wilde (2016) find no evidence of differences in pre-trends for output growth, labor growth and product variety at different levels of aggregation. Following the reform, output and employment increased in these markets due to increased entry and expansion of firms that were previously constrained by the capital threshold. More relevant to this paper, Galle(2016) finds a fall in markups post dereservation without any pre-trends, resulting in pro-competitive gains. Singh (2017) provides evidence of a significant fall in output prices both in short-term and medium-term post reform (using the CMIE Prowess data of only publicly listed firms). This fall in prices could be driven

[11]Firms could expand beyond this threshold if they export at least 50% of their output. Also, firms that exceeded this threshold prior to the policy implementation could continue production but were restricted from expanding.

[12]This capital threshold expanded over the 30 years until it reached the 10 million limit in 1997

[13]Reservation was intended to protect SSI from competition. But, with the possibility that large undertakings could operate in the market under certain conditions, there was also concern of market structure tilting to a dominant firm with competitive fringe, creating deadweight loss.

by both increasing competition and increase in quantity supplied. My paper leverages the dereservation episode to study the spillover effects of such distortions on linked markets.

The dereservation provides us with a rich variation in policy-induced misallocation across time and industries. Availability of detailed firm-level data allows me to explore the distributional effects and identify the channels through which distortionary policies lead to lower aggregate productivity while controlling for firm and industry fixed effects, as well as state and product-specific trends. As this paper studies suppliers' and customers' reaction to such policy changes, it uses plausibly exogeneous variation in upstream and downstream exposure as well. Section 4 contains a description of the data. Of the 1300 reserved products, nearly 50 percent of the products (658 products) were reported as being used as intermediate inputs in production, helping identify the downstream effects. Of the firm-input observations, 27 percent of the observations are from the reserved product markets. In the upstream, 40 percent of never reserved firm-output observations supply inputs to the reserved markets. I find no pre-trends in output or prices in linked markets prior to the reform. Finally, with price and quantity data for both inputs and outputs at the detailed product-firm-year level, I back out markups and productivity using the product-function approach to study the reallocation gains and role of market power. This Indian case thus offers an excellent setting to explore the role of linkages in bolstering the effects of deregulation.

3 Stylized Framework

Before presenting the empirical analysis, l describe a simple partial equilibrium model to build intuition on how a bottleneck in the supply chain can have distributional consequences when market structure is heterogeneous across related markets. Without loss of generality, I assume there are only three levels of imperfectly competitive markets that are combined in sequence to make a final good: an upstream supplier market u, intermediate reserved market r facing size-restrictions and downstream customers d, and where both basic inputs and final retailing are separated from firms that integrate intermediate inputs within the supply-chain[14]. My goal is to show how eliminating size-restrictions in R can transmit upstream and downstream, with ambiguous responses. With this aim in mind, I combine insights from canonical model of supply chain proposed by Spengler(1950) with variable markups. The network of interest is fixed (i.e. downstream firms transform the upstream good in fixed proportions into a final

[14]I expect the transmission mechanisms proposed in the paper to work by the same channels through higher order linkages. However, for clarity and brevity, I focus only on the first order linkages. Investigating the effect of concentration across the whole economy is a subject for future research, although it would be complicated by the Leontief inverse matrix mixing together ω's from all sectors.

product) and exogeneous and substitution effects from outside this network may be ignored[15]. Finally, there is no monopsony power whereby downstream firms do not exhibit market power in the upstream market[16].

3.1 Intermediate Goods market

The production side of the economy consists of multiple intermediate goods markets, each with a finite number of firms. Here, I employ a few simplifying assumptions. Firms are profit maximizing and labor is the only primary input. The firm e in market i combines labor L and other market goods x_j to produce q_{ie} units using the following Cobb-Douglas production function:

$$q_{ie} = z_{ie} L_{ie}^{1-\gamma_i} (\prod_{j=1}^{n} x_{ije}^{\omega_{ij}})^{\gamma_i} \qquad (1)$$

where x_{ije} are the intermediate goods from market j used by firm e in market i with ω_{ij} capturing the fixed input share of market j's goods needed to produce market i's production, z_{ie} is the firm-specific hicks-neutral TFP and $\gamma_i = \sum_{j=1}^{n} \omega_{ij}$ (i.e. production function exhibits constant returns to scale) [17]. Market real output is given by $Q_i = (\sum_{e=1}^{E} q_{ie}^{\frac{\sigma_i - 1}{\sigma_i}})^{\frac{\sigma_i}{\sigma_i - 1}}$. Labor supply is exogenous and labor market clearing is given by $L = \sum_i \sum n L_{ie}$.

In this framework, as larger firms are more likely to be regulated and penalized, the cost of reservation can be approximately written as an output distortion:

$$\max \pi_{ie} = (1 - \tau_{ie}(q_{ie})) P_{ie} q_{ie} - w_i L_{ie} - \sum_{j=1}^{e} P_j x_{ije}$$

where $\tau_{ie} \geq 0$ if a firm-specific wedge that distorts output and is increasing in its quantity[18]. Solving for the firm's problem, price-setting rule is the standard markup over marginal cost based on the firm-specific elasticity of demand $\epsilon_{ie} = -\frac{\partial q_{ie}}{\partial P_{ie}} \frac{P_{ie}}{q_{ie}}$ and markup elasticity $E = \frac{\partial \epsilon}{\partial p_e} \frac{p_e}{\epsilon}$

[15]Here the IO linkages are interpreted as technology. I abstract from general equilibrium considerations that would introduce interactions in product or factor markets across supply-chain. See Goulder and Williams III (2003) to derive empirically implementable formulas for incidence in the presence of pre-existing distortions in all other markets and formulate the general equilibrium effects.

[16]I find no evidence of monopsony power in this setting. Additionally, this is a standard assumption in the literature on vertical oligopolies, e.g. Ghosh and Morita (2007).This property approximately holds if the upstream sector serves a large number of independent downstream markets so that a quantity change by a firm in one of these downstream markets has a negligible effect on the price of its input.

[17]Labor can be thought of as encompassing all the primary inputs including capital K_{ie} with the following setup $L_{ie}^{\alpha_i} K_{ie}^{1-\alpha_i}$. I suppress capital to simplify the notation.

[18]τ_{ie} continuous function that does not exactly capture the policy studied in this paper. However, the policy was not a rigid cutoff as observed in both the resulting firm-size distribution and degree of flexibility in the capital constraints.

[19]:

$$P_{ie} = \underbrace{\frac{\epsilon_{ie}}{\epsilon_{ie}-1}}_{\text{Markup}} \underbrace{\frac{1}{1-\tau_{ie}}}_{\text{SDD}} \underbrace{[(\frac{w_i}{1-\gamma_i})^{1-\gamma_i}][(\prod \frac{P_j}{\omega_{ji}})^{\omega_{ji}}]^{\gamma_i}[\frac{1}{z_{ie}}]}_{\text{Marginal cost}} \tag{2}$$

There are three important takeaways from this solution. Firstly, without a size distortionary policy, more productive firms producing a differentiated good with a lower marginal cost will produce higher quantity within a market. Second, larger policy distortions or market power will force firms to charge a higher price. Finally, a positive τ exerts a disproportionately higher penalty on high-productivity firms. Hence, the key result is that size-constraints create a production bottleneck by restricting growth of productive firms. A point to note is that these distortions are not taxes - there is no revenue to rebate - rather frictions that prevent firms from equalizing marginal costs and marginal products.

Let $\phi_{ie} = \frac{1-\tau_{ie}}{\mu_{ie}}$ be firm-specific wedge between its marginal cost and marginal revenue where μ_{ie} is a firm-specific markup that captures the market-power of the firm. Hence, high (marginal) product can be indicative of both market power and constraining output distortions. A producer with monopoly power may produce less than the efficient level but charge a higher markup. A decrease in ϕ_{ie} results in fall in output with $\phi_{ie} \to 1$ indicating lower distortions, either through lower τ or markups.

Testable Prediction 1 - *(Reserved markets): Removal of size-restrictions will reduce output distortions τ_{re}. This reallocates production to initially more productive firms, which are constrained by the policy. Market-level aggregate output increases and prices decrease.*

The key factor for the above prediction is that high-productive firms are the ones constrained by the size-restriction, Hence, eliminating the size-restriction will reallocate production to these high-productive firms. The effects on markups are theoretically ambiguous as competition could increase or decrease within the market. Existing empirical evidence and the institutional context points to increased competition once the size-constraints were removed (i.e. $\phi_{re} \to 1$).

Rewriting Equation (2), where $\tilde{mc}_{ie}$ is the marginal cost of primary inputs (i.e. labor):

$$P_{ie} = \frac{\epsilon_{ie}}{\epsilon_{ie}-1}(\omega_{ji}p_j + \tilde{mc}_{ie})$$

With constant returns to scale, sector-level marginal cost is also equal to the average cost $mc_i = \sum_{e=1}^{E} mc_{ie}s_{ie}$. Then, aggregate wedge for market i ϕ_i is given by:

[19]E is positive (negative) when demand is strictly convex (concave) and zero for linear demand.

$$\phi_i = (\sum_{e=1}^{E} \phi_{ie}^{-1} s_{ie})^{-1} \qquad (3)$$

The aggregate wedge is a revenue-weighted harmonic mean of firm-level markups and output distortions where $s_{ie} = \frac{p_{ie}q_{ie}}{P_i Q_i}$ is the market share of the firm. Here, the price index of market i, P_i is given by:

$$logP_i = log\phi_i + log\tilde{mc}_i + \sum_{j \neq i} \omega_{ji} log\phi_j \tilde{mc}_j \qquad (4)$$

Therefore, when production involves more than one vertically-related step, the relationship between costs and final prices will depend on the combined effect of the separate distortions faced and markups set by the vertically-related firms. This is commonly referred to as "double-marginalization" in the supply-chain literature. If upstream and downstream markets are close to perfectly competitive (i.e. $\mu \to 0$) or there are no policy distortions (i.e. $\tau \to 0$), these higher-order effects can be ignored.

To capture the upstream demand and downstream supplier effects, I generalize the notation as follows. An individual producer in each vertically linked market faces an inverse demand function given by p where:

$$p = P(q, \alpha)$$

where p is the price, q is quantity, α contains exogenous variables that affect demand such that $P_q < 0$ and $P_\alpha > 0$. Each firm faces a constant marginal cost $c = C(z, \eta)$ where z is the unobserved productivity and η is the intermediate input costs with $C_z < 0$ and $C_\eta > 0$.

Taking the uniform input prices as given, the resulting first-order condition for profit maximization is:

$$\frac{d\pi_{ie}}{dq_{ie}} = \underbrace{P(q, \alpha) + P_q(q, \alpha)q}_{\text{Marginal revenue}} - \underbrace{c}_{\text{Marginal cost}} = 0$$

where $q = Q(\alpha, z, \eta)$ is firm output.

3.1.1 Upstream effects

When $\phi_r \to 1$, there is a positive demand shock for upstream markets u. Solving profit maximization for firms in reserved market r and aggregating:

$$P^u = \gamma_r \omega_{ur} (\phi_r \frac{P^r Q^r}{x_{ru}})$$

such that inverse-demand function P^u shifts out. Let α be the firm-specific demand shock for upstream suppliers such that $P^u_\alpha > 0$. Then,

$$Q^u_\alpha = -\frac{MR_\alpha}{MR_q} = -\frac{P_\alpha + qP_{q,\alpha}}{P_q(2+E)}$$

Firms respond heterogeneously to their demand shock depending on their elasticity of demand and demand curvature, with firms facing less elastic demand and higher markup elasticity having smaller output growth. Firm-specific markups would also change:

$$\mu^u_\alpha = \underbrace{\frac{P^u_\alpha}{c}}_{\text{Direct effect}} + \underbrace{\frac{P^u_q q^u_\alpha}{c}}_{\text{Indirect effect}}$$

The first term captures the positive direct effect on prices via a shift in the demand function. The second term is the negative indirect effects due to an increase in production that decreases prices. The latter effect comes from entry and will take time to come into effect. Hence, the effects of demand shocks on markups are ambiguous and would require an empirical analysis. Markups will increase as long as the ratio of the elasticities of the inverse demand function and of output both with respect to demand shock is greater than the markup elasticity. Here, market power channel has important implications for output and prices. If a demand shock affects firm's demand elasticity, this can potentially generate feedback effects on the markup and markup elasticity. Under many demand systems, productive firms will face lower demand elasticities and hence feature higher markups and markup elasticity. This would then imply higher markup increase for larger and more productive firms in response to a demand shock.

Testable Prediction 2 *(Upstream Markets): When distortions in the reserved market decreases, upstream suppliers experience a positive demand shock. Output increases. More productive firms will increase prices relatively more than less productive firms.*

Note the prices will rises if and only if the price elasticity falls and there is no firm entry. These effects will be stronger in upstream markets that are more exposed to reserved markets as inverse demand shifts out further[20]. If market shares capture the market power of firms (as in Atkeson and Burstein (2008)), then larger, more productive firms will have higher market power in more concentrated markets. These firms would respond to the demand shock by increasing markups more and consequently have lower output growth.

[20]This is in line with the centrality measure emphasized by Brassi (2018), Baquee (2018) and Acemoglu et al. (2012), whereby markets that are important customers or suppliers will have large reallocation effects.

3.1.2 Downstream effects

When $\phi_r \to 1$, there is a uniform input cost shock for downstream customers d as price of intermediate inputs decreases (see Equation 3). Summarizing the size of input cost shock by η, downstream customers have the following markup response:

$$\mu_\eta^d = -\mu \frac{C_\eta^d}{c} + \frac{P_q^d Q_\eta^d}{c}$$

The effect on markups is theoretically ambiguous in this case as well. However, there is consistent evidence in the literature of increasing markups indicating incomplete pass-through. The pass-through elasticity of a cost reduction for d is given by:

$$\frac{\partial p_d}{\partial p_r}\frac{p_r}{p_d} = (\frac{1}{1+\frac{E}{(\epsilon-1)}})\frac{\omega_{dr}p_r}{\omega_{dr}p_r + \widetilde{mc}_d}$$

As Weyl and Fabinger (2013) show, this pass-through is complete for perfectly competitive markets and decreases with monopolization of the market. Firms facing lower demand elasticity would charge higher markups and exert market power via final consumers with uniform intermediate input cost reductions. For example, if indeed demand elasticity decreases with firm productivity, then a cost shock could lead to markup adjustments and lower pass-through for more productive firms. See appendix C for proof using the Atkeson and Burstein (2008) model. This heterogenous cost-pass through then logically generates heterogenous quantity response to a supply shock.

Testable Prediction 3 *(Downstream Markets): When distortions in the reserved market decreases, downstream marginal costs decreases. Output prices decrease while quantity increases. A reduction in intermediate input prices increases markups due to incomplete pass-through with stronger effects for more productive firms.*

Again, the effects for downstream markets increase with exposure to the reserved market, measured by ω_{dr}. The markup variations could lead to efficiency loss within the market if the dispersion in markups is large enough to reallocate production to initially low markup firms because they increase markup by less. The framework in Appendix C in which marketshares determine markups would suggest that more concentrated markets will see larger markup dispersions. In the next subsection, I show how any changes in the markups and the resulting markup dispersion in linked markets can diminish the aggregate productivity gains.

3.2 Aggregate productivity implications

The impact of distortions on aggregate TFP can be broken down into two components. First, some firms become more productive and increase their output given the initial distribution of resources increasing the average productivity[21]. Second, the focus of this paper, the distribution of resources across producers shifts in response to the shock, leading to over-production by some firms and under-production by others. This change in "allocative efficiency" also affects aggregate TFP. In particular, the heterogeneity in markups is also important because of its implications on allocation. As in Chari et. al (2007), distortions affect allocations relative to the efficient level through two channels: aggregate efficiency wedge that is a result of misallocation of inputs throughout the supply-chain and labor wedge between the marginal product of labor and the real wage that acts like an input tax and reduces output relative to the efficient level. Recall, *Labor wedge* ϕ_i for market i is given by:

$$\phi i = (\sum_{e=1}^{E} (\frac{\mu_{ie}}{1-\tau_{ie}})^{-1} s_{ie})^{-1}$$

Then, as in Hsieh and Klenow (2009), any policy that increases the dispersion of markups or marginal products reduces the aggregate TFP by increasing the dispersion of revenue productivity (TFPR):

$$TFPR_e = P_e z_e = P_e \frac{Q_e}{L_e^{1-\gamma} x_e^{\gamma}} = \mu_e (\frac{MPRL_e}{1-\gamma})^{1-\gamma} (\frac{MPRM_e}{\gamma})^{\gamma} \tag{5}$$

where $MPRL_{ie}$ denotes marginal revenue product of labor and $MPRM_{ie}$ denotes marginal revenue product of materials, both derived from Equation (1):

$$MRPL_{ie} = 1 - \gamma_i \frac{P_{ie} q_{ie}}{L_{ie}} = w_i \frac{\mu_{ie}}{1-\tau_{ie}} \text{ and } MRPM_{ie} = \gamma_i \frac{P_{ie} q_{ie}}{X_{ie}} = p_j \frac{\mu_{ie}}{1-\tau_{ie}}$$

Market frictions distort the use of sectoral inputs yielding higher marginal products and resulting in less-than-optimal output. $TFPR$ summarizes the impact of distortions on an establishment with higher revenue productivity than industry average indicating a higher level of distortions. With a constant-elasticity-of-substitution demand:

$$TFP_i = \frac{TFPR_i}{P_i} = [\sum_e (z_{ie} \frac{\phi_i}{\phi_{ie}})^{\sigma-1}]^{\frac{1}{\sigma-1}}$$

where σ is the elasticity of substitution between different varieties. If the increase in output across the supply-chain is driven by reallocation of inputs to more productive firms (i.e. $\phi_{ie} \to 1$ for most productive firms), then aggregate TFP increases. However, as previously shown, firms in linked markets could respond by changing their markups. If the increased markup dispersion is driven by most productive producers and a less-than-optimal share of inputs is allocated to them, TFP gains will diminish. That is, if the reallocation of inputs

[21] Technical productivity growth could arise from entry, technology adoption, economies of scale etc.

across the supply-chain is driven by increasing market share of profitable firms who are also more productive, then the productivity gains would be smaller.

4 Empirical Strategy

In this section, I present the data and the empirical specification to quantify the first-order effects of liberalization. First, I identify the effects on output prices and quantity in reserved market. Then, I proceed to describe the methodology for identifying upstream and downstream firms and present evidence that confirms our predictions of transmission to downstream markets as a supply shock and to upstream markets as a demand shock. Finally, I describe the methodology for calculating markups and productivity that will be used to study the distributional effects.

4.1 Data

The empirical analysis mostly relies on the Annual Survey of Industries of India (ASI) from 2000-2001 through 2012-2013[22]. The ASI is a repeated cross section representative of formal establishments. with large establishments surveyed each year and smaller establishments surveyed with a probability that depends on their specific state and 4-digit industry block, with a minimum sampling probability of 15%[23]. Recent changes in policy have allowed researchers to track establishments who were sampled multiple times, thereby creating a panel version of the ASI that goes back 1998. I use this panel version for the establishment-level analysis and aggregate the firm-level data using the sampling weights for the product-level analysis[24]. Finally, using the panel version of the data to examine misallocation mitigates concerns about measurement errors as well as the potential for adjustment costs to generate the cross-sectional dispersion in the marginal product across firms rather than idiosyncratic

[22] I will refer to these years as 2000 through 2012 hereon. ASI uses the accounting year, which runs from April 1st to March 31st. For products de-reserved towards to end of an account year, I do not count these products as de-reserved until the following year.

[23] Formal establishments include manufacturing plants employing twenty or more workers and not using electricity, or employing ten or more workers and using electricity. Large establishments are those with 200 or more workers until 2003-2004, and 100 or more since then.

[24] Firm-level regressions may not be ideal because smaller establishments are sampled less frequently than larger ones. However, 57 percent of the establishments observed making a reserved product have at least one observation both pre and post de-reservation. I use these incumbent firms for the firm-level DID estimates ensuring the composition of individuals of the two groups remain unchanged over time. Secondly, there is no reason to expect that there is differential sampling by firm size between reserved and never-reserved markets. Furthermore, the SSI cutoff is capital-based whereas the sampling frame is labor-based. Hence, I still observe firms that have less capital but a large labor more frequently. Finally, I complement the analysis with product-level analysis and the results remain robust.

policy distortions.

The basic unit of observation in the ASI is an establishment. I treat each establishment as a separate firm as most establishments are the only plant in their firm[25]. The main advantage of the ASI is that establishments report products they produce and inputs they use at the detailed 5-digit product classification (ASICC), which has about 5,500 possible products comparable to the 5-digit SIC product definition collected for U.S. manufacturing plants and is at the level of product reservation. Each establishment reports the quantity of the product it uses and produces and its respective value (before taxes and distribution expenses) which can be used to compute prices. Each product quantity is supposed to be reported for a standardized unit (kilograms, numbers, etc.) allowing for comparison across firms within product markets and easier aggregation[26].

The dataset contains around 30,000 establishments per year with 385, 873 unique firm-year observations in total. For these establishments, we have a total of 1,436,347 raw material input entries, which is 3.72 entries per firm on average over the entire period. These input-using firms also report data on sales quantities and values with 573,595 output entries, which is 1.5 entries per firm on average. 94% of the firms report to use more than one input and 43% of the firms sell more than one output.

Data on the dereservation dates and their respective product list is readily available from the Ministry of Micro, Small and Medium Enterprises.

4.2 Specification

Event study design

I now describe the empirical strategy to test the dynamic effects of dereservation. To start, I am mainly interested in studying the overall quantity and prices effects as this will confirm if dereservation had a substantial impact on the product markets. I start with the following event-study on dereservation equation of the following form where V_{iet} is the log of outcomes (unit prices, output, revenue, markups, market shares) of market i in establishment e in year t:

$$V_{iet} = \alpha_0 + \sum_{k=-4}^{5} \beta_m 1[t = E_{iet} + \tau] + \alpha_{ie} + \alpha_t + \epsilon_{it} \quad (6)$$

[25]ASI contains very little information about each establishment's parent firms. Less than 5% of the firms do joint returns.

[26]Another project that uses this information is Kothari (2013). In the ASI, all plants reporting a certain product are supposed to report quantities in the same units. However, there are clear cases in which plants are misreporting quantity units. I use a modified version of his algorithm to address the misreporting issues. More details in the Appendix B.

I define the time at which the establishment e is first exposed to the dereserved product market directly or indirectly as E_{iet}. I also bin up the end-points and normalize $\beta_{-1} = 0$. The control group serves to absorb any secular trends in demand/supply side of the Indian economy. Aggregate product-level output is constructed using reported output at the establishment-level and applying the sampling multipliers to all infrequently sampled firms. For the event-study specification, I restrict the sample to a balanced sample of incumbent plants, which includes all plants whose main product category was reserved prior to reform.

Difference-in-Difference setup

$$V_{iet} = \alpha_0 + \beta_{iet} Dereserv_{it} \text{ x } Exposure_i + \alpha_{ie} + \alpha_t + \epsilon_{iet} \qquad (7)$$

$Dereserv_{it}$ is an indicator that that equals 1 if the product is exposed to the dereserved market directly or indirectly (through IO linkages). All regressions include Firm- Product fixed effects and Year fixed effects and weighted by the inverse sampling weights, provided by the ASI. $Exposure_i$ is a measure of the upstream/downstream exposure to the reserved markets and is determined using the pre-dereservation firm-level input-output correspondence table [27]. For upstream and downstream markets, I account for demand side shocks that could be correlated with dereservation by eliminating firms that are selling products on the output side in the reserved market. Errors are clustered at the firm level to adjust for heteroskedasticity and within-firm correlation over time. For the aggregate product-level analysis, I run the same regression as above but with product fixed effects instead of firm fixed effects weighted by the initial labor shares and errors clustered at the product-level.

Identifying IO linked markets

To study the transmission through IO linkages, I need to identify firm-outputs that are made from reserved inputs for downstream customers and vice versa for upstream firms. Input-output table at the detailed product level data is not available. Firm-level data lists inputs used and products sold separately. Therefore, I construct a binary input-output correspondence that specifies whether an input is used in the production of a particular output or not by using data only from the single-product firms. This is based on the assumption that all the inputs that single-product firms report to use enter the production of this single output. I map this correspondence to the multi-product firms.

A natural measure for a market's exposure to the reform is its share of input costs from reserved markets to total costs in the case of downstream effects, and the share of upstream

[27] $Exposure_i = 1$ for the reserved product markets.

sales that is used as inputs in manufacturing by reserved markets. Using the approach in Acemoglu et al. (2015) and leveraging the detailed product -level data at the firm-level, I construct measures of upstream and downstream exposure to reserved markets. To account for the fact that I do not observe every plant in India in every year, I combine the samples from every year, and for each firm keep its most recent pre-dereservation observation. Given the design of the ASI, this should reflect a census of all manufacturing firms, albeit a census taken over several years (since there are 6 years of pre-program data for most of the reserved products and with a rotating sampling frame, each existing firm should have been surveyed at least once in the period). All the exposure measures are calculated prior to the first episode of dereservation for the relevant market.

For upstream markets, I measure exposure of product market u as the lagged share of input usage that goes into reserved product markets r. Here, $Sales_u$ refers to the sum of sales for r from output that is directly consumed as intermediate inputs by downstream firms with $Sales_{ur}$ going into the reserved product market:

$$Exposure_u^{Upstream} = \sum_r \frac{Sales_{ur}}{Sales_u}$$

Average exposure of upstream markets is 25 percent with a median of 8 percent. For downstream markets, more exposure to reserved supplier market r should be more inhibiting for firms in downstream markets d. I utilize similar method as above to determine the exposure for downstream markets d:

$$Exposure_d^{Downstream} = \sum_r \frac{Sales_{rd}}{Sales_d}$$

Average exposure of downstream markets is 16 percent with a median of 6 percent. Around 10 percent of firm-product observations are in both markets (i.e. R and D, R and U, U and D) with 3 percent of observations in all three markets. For the empirical analysis of linked markets, I drop observations that also belong to the reserved market [28].

Note that downstream and upstream industries could be exposed to multiple reserved products with different dereservation dates. I sum up the exposure to all reserved products prior to the first dereservation episode. Secondly, the upstream and downstream exposures are fixed at the pre-dereservation era so the effects by exposure are simply a function of shocks in connected markets working through a pre-determined IO network. This assumption is reasonable in the short to medium-run where elasticity of substitution between different

[28] Around 34 percent of observations are purely in control group. Given that 40 percent of the establishments are multiproduct, then it is possible that multiproduct firms react differently post-deservation. Tewari and Wilde (2018) shows the effects to be stronger for multiproduct firms as these firms are able to reoptimize their product scope.

inputs is close to 0 (see Boehm et al. (2018) for example). Furthermore, aggregate IO tables have not shown significant modifications in the long-run. Finally, I standardize the exposure variables so that a unit increase corresponds to a one standard-deviation change in the positive direction (i.e. more exposure).

4.2.1 Production function estimation and markups

The analysis of distribution effects and the resulting allocative efficiency gains would require estimates of markups and productivity [29]. I compute time-varying, firm-product level markups using structural methods developed by De Loecker and Warzynski (2012) and De Loecker et al. (2017). These estimates combine plant-level production data with assumptions on firm cost minimization to back out marginal costs as the difference between the price and markup. The main advantage of this methodology is that it does not require functional-form assumptions about preferences or the competitive environment. Here, a firm's first order condition under Cobb-Douglas production function implies that the plant's markup equals the output elasticity of a variable input like materials divided by the revenue share of that input:

$$\mu_{ist} = \frac{\theta^x_{ist}}{\alpha^x_{ist}}$$

where θ is output elasticity of materials and α is cost share of materials. Intuitively, conditional on the output elasticity of labor, firms that spend a higher share of their revenue on materials set lower markups. The first step is to estimate the output elasticity of a variable input. Output elasticities are estimated by proxying for unobserved productivity with the firm's material inputs (Levinsohn and Petrin, 2003, Ackerberg, Caves and Frazer, 2015) and a flexible translog, gross-output production function. TFP is the residual of this estimated production function. Details are presented in Appendix D.

Table E.2 shows the production function coefficients and the median markup by NIC 2-digit industry. The median markup for the whole sample is 21 percent, consistent with past estimates. In the first step, I establish that higher markups are correlated with both higher TFP, higher market share and more employment. Lower marginal costs are correlated with higher TFP as well as higher market share. Finally, using the regression setup of (7), I find that downstream markets report a significant fall in marginal costs while upstream markets

[29] Markups informs us that the margin of revenue over variable costs has increased. It does not necessarily imply that firms are making higher economic profits, a necessary condition for market power. For example, if a technological change increases the fixed cost but reduces the variable costs, then the rise in markups would not imply higher market power. I find lower volumes with higher markups only in more concentrated markets, lending confidence to a market power interpretation

report a significant rise in markups with no changes in marginal costs, giving confidence to the proposed transmission mechanism.

4.3 First-stage effects

4.3.1 Effects on reserved markets

Firstly, I present evidence on the impact of dereservation on both output and prices in the dereserved markets using the event-study specification. Figure 1 demonstrates an increase in output with a corresponding fall in output prices following the reform. As soon as dereservation is enforced, there is an immediate and significant decline in prices with output growing more slowly. In subsequent periods, the changes in output prices and sales becomes stronger reflective of the time needed for establishments to expand and enter a new product market. These results are in line with the theoretical prediction of fall in prices, driven by both increasing competition and fall in distortions[30]. Finally, there are no significant differences between treated and control group prior to dereservation, lending confidence to the identification set-up.

Next, I aggregate the outcome variables to includes all establishments in a given year. Aggregated product-level effects of dereservation are presented in Table 1. De-reservation leads to an average increase of 32% in quantity and 24% increase in revenue. The fact that quantity increased more than revenue suggests that prices fell by nearly 8%, consistent with the estimates of input prices reported by downstream firms as well the firm-level evidence presented in Figure 1. These large effects are all significant at the 10 percent level. Secondly, the increase in labor is less than the increase in output, leading to a increase in labor productivity. Finally, there is substantial growth in the number of establishments operating within the dereserved market. These results suggest that dereservation lead to the entry and growth of more productive firms, providing support for my hypothesis that reservation reduced misallocation[31].The magnitudes reported here are similar to results presented in Martin et al. (2017), although I use a longer sample that captures the medium-run effects[32]. These results are robust to the inclusion of statexyear FE as well as nic3digit x year FE.

[30]In the appendix, I present results of falling HHI within the dereserved product markets that suggests increased competition

[31]Exit is difficult to measure in this dataset because of the rotational panel.

[32]Their analysis uses data from 2000 - 2007. With most of the dereservation episodes happening between 2006 - 2008, they only capture the immediate effects. Additionally, their analysis is at the firm-level contrary to my analysis at the firm-product level. This can explain the relatively smaller magnitudes in establishment growth and a fall in labor productivity they observe.

4.3.2 Impact on IO linked markets

Theoretically, the increase in output and decrease in output prices for reserved markets, reduces the marginal cost of downstream sectors and acts as a supply shock. As output increases, there is increasing demand for intermediate inputs resulting in a demand shock for upstream sectors. In this section, I verify the propagation of this reform episode through IO linkages holds empirically.

Upstream suppliers: First, I look at the upstream markets identified as inputs by establishments producing a single reserved product. When I classify an establishment as making an output that is used by reserved market as input, the output could go to multiple reserved markets with different years of dereservation. Hence, in the event-study specification, the indicator is equal to 1 starting from the first year of deresrevation[33] I find an increase in output price and quantity post-dereservation in the upstream market. These effects become stronger over time and there is a jump in coefficients three years after dereservation, in line with increased entry and falling HHI observed in the reserved market. Again, the magnitudes are consistent with the effects reported by reserved markets as well, lending support for evidence presenting using this data and methodology.

In the event-study specification, I imposed a dummy variable i.e. any non-zero exposure to the dereserved sector would be identified in the treatment group post-dereservation. I pursued this approach because of concerns with misreporting. Here, I study an alternate measure of treatment that estimate the effects by the intensity of exposure. This allows me to ensure results from the event-study is robust to accounting for exposure.

The coefficient of interest is the interaction of log measure of $Exposure^{Upstream}$ with the $UpDereserv$ dummy that equals to 1 from the year the first reserved customer market is dereserved. For the upstream markets, a 1 S.D. increase in exposure to reserved market (i.e.18% of intermediate input sales is to the reserved market) leads to 6% increase in sales with 2% resulting from increase in prices and the rest driven by increase in quantity at 4%.

Downstream customers: The first step for downstream market is to determine the effects on input prices and quantity consumed. For this purpose, a dummy variable on dereservation is a sufficient measure because this is a direct supply shock and we have information on the product-wise input prices and quantity. I compare values or prices of inputs have been dereserved to control group of inputs that have no history of dereservation before and after the reform episode.

[33]This seems reasonable as most of the dereservation over a span of 5 years between 2003 and 2008, hence there is substantial overlap in exposure to the reform. In addition, the results are robust to alternate specification such the using dereserved year of the main customer market and median dereservation year for each product market. Results are available upon request.

I need a comparable control group of firm-input to test the effects of input prices and quantity. For this, I do a matching between treated and untreated inputs at the firm-input level. In the matching, I verify that the treated inputs in treated firms are similar to treated inputs in control firms on two dimensions: same trend in input use in terms of quantity and value and belong to same 3-digit NIC industry. In addition, by including firm - input fixed effects, I account for observable and unobservable sources of heterogeneity at the firm-input level that may affect raw material input usage. My aim is not to explain input levels, but instead study changes in input usage from dereservation.

I find a 9% fall in input prices reported by downstream firms once the intermediate input is dereserved. The effects become stronger over time and are similar in magnitude and trend to the output prices reported by the reserved markets. Looking at input quantities, there is a 24% increase in input quantity consumed by downstream firms. These results give confidence that the data quality is consistent across the vertical chain as the input trends reported by downstream markets matches the output trends reported in reserved markets.

Given that firms report fall in input prices and increase in input consumption, then one can expect changes in the prices and quantity produced as well. If there is complete - passthrough, then fall in output prices capture the magnitude of fall in marginal costs. However, given the extensive evidence of incomplete pass-through in various contexts (including in India using the same dataset), it would be reasonable to be expect the observed changes in prices to reflect only a fraction of the changes in marginal co[34]. Table 2 presents the results using the exposure measure for downstream firms with DID setup. The coefficient of interest is the interaction of log measure of $Exposure^{Downstream}$ with the $InputDereserv$ dummy that equals to 1 from the year the first reserved input is dereserved and 0 otherwise. I find that firms in downstream market with 1 S.D. greater exposure to reserved supplier (i.e. 17 percent of input share is from the upstream market) experience 1% growth in sales that is driven by a 4% increase in quantity and a fall in output prices of 3%.

Hence, the upstream and downstream effects of dereservation are robust to the definition of the treatment variable. Finally, it is plausible that upstream and downstream industries connected to the reserved product market might be facing other correlated demand and supply shocks that differently affects its performance and input/output choices. We find no substantial trends in the input/output choices prior to dereservation, but firms reallocate their inputs (outputs) towards dereserved products in the downstream (upstream) sectors

[34]Technically, pass-through can be more than 100 percent with log-convex demand. However, there is consistent empirical evidence that counters this theoretical prediction including the vast literature on exchange rate pass-through. See Hellerstein (2008), Nakamura and Zerom (2010) and Feenstra, Gagnon and Knetter (1996) for example.

after dereservation.

4.3.3 Feedback effects from linked markets

Finally, as a first pass, I test if the output growth varies by market power in the upstream suppliers and downstream customers. If firms in these vertically linked markets have market power, they could extract a larger share of the Ricardian rent and the resulting feedback effect potentially could reduce the gains from dereservation. I interact the *Dereserv* dummy with the pre-dereservation weighted upstream and downstream HHI. The HHI are weighted by the input shares (as a fraction of total costs) from upstream suppliers and input shares for downstream customers. Results are presented in Table 4. When suppliers are concentrated, output growth for dereserved markets is significantly smaller. This is suggestive of increasing input costs mitigating the growth. There are no significant feedback effects from downstream, perhaps because relatively fewer firms are customers of reserved products.

5 Distributional effects

In this section, I test the model's predictions about reallocation and the aggregate misallocation consequences of upstream and downstream distortions using firm-level behavior to support the results. When firms differ in productivity, the distribution of inputs across firms affects allocative efficiency within the market. I test the distributive effects of dereservation on firms in the production network. According to our theoretical framework, there are two sources of misallocation - policy distortions that implicitly taxes large firms and markups. This misallocation drives a wedge between the revenue and output as larger and more productive firms are underproducing relative to smaller and less productive firms. I start of the section by describing the regression frameworks used in this analysis. I will use a difference - in-difference (DID) equation of the following form for establishment e in year t:

$$V_{est} = \beta Dereserv_{st} X_e + \alpha_{es} + \alpha_t + \epsilon_{est} \tag{8}$$

Here, I interact firm-level productivity X_e with the dummy for dereservation *Dereserv* from the previous section. For upstream (downstream) markets, I use the *UpDereserv* (*DownDeresrev*) dummies respectively. The results are restricted to incumbent plants in the production network. All regressions include year FE and product-firm FE. Errors are clustered at the firm-level.

5.1 Reserved Market

To casually determine if there is reallocation of market shares towards more productive firms, I interact firm-level productivity prior to dereservation with $Dereserv_s$ and examine its effects on the market share. Results are presented in Table 5. I find that amongst the incumbent firms, there is evidence of market reallocation as the most productive firms experience the sharpest increase in their market revenue share: a firm with 10 percent higher productivity witnesses a 0.8 percent increase in market share[35].These results are robust to including firm-level controls such as capital, age and labor as well as state-specific trends that capture the local demand effects and industry x year FE that control of any factors that affect demand or supply of all firms within a industry in a year (e.g. trade shocks).

5.2 Effects of market power - Upstream

I have found evidence thus far for the first order comparative static predictions, including the positive demand and supply shocks for downstream and upstream markets as well as reallocation in the reserved markets itself. The next step is to determine if there is any redistribution in upstream markets. In particular, I analyze if the strategic decisions on pricing and output of upstream suppliers depends on their market power. For the rest of analysis, I use the fact that productivity of the firm is the source of its ability to price over the marginal cost and the HHI of the market captures the market's potential to raise markups. Firstly, I split the sample of firms by the median HHI (for statistical power) to test if there are any differences in firm behavior post a demand shock by the market power in the market[36]. In examining the reallocation measures below, I focus on the effects of dereservation on reallocation across incumbent firms. While this is undoubtedly missing the dynamic effects of reserved markets if more firms enter or exit, as shown in Table A.11, I do not observe significant growth in the number of establishments for upstream or downstream firms. This alleviates concerns of entry driving the effects and instead points to reallocation amongst incumbents as the dominant effect.

In Table 6, I find that average output prices increase, but the effects are significantly and statistically larger in more concentrated markets. Average output increases in all markets with no significant differences by market concentration. This suggests that demand is highly

[35] I find that for firms that are 10 percent more productive within an upstream market, their market share increases by 0.4 percent post-dereservation but I find no such effects for downstream firms. Results are not presented here for brevity but are consistent with the rest of the analysis.

[36] HHI is calculated as the sum of squared market shares that are each weighted by the sampling multipliers from the ASI in the base year. While I use HHI calculated at the product-level, the results are robust to using more aggregated HHI at the NIC 5-digit and NIC 4-digit level that is an annual census of manufacturing in India.

inelastic for intermediate inputs that despite the increase in the prices, the output remains constant. This is consistent with evidence in the literature that finds inputs to be Leontief in production and elasticity of substitution being close to 0 (Boehm et. al 2018). Hence, more concentrated upstream markets are just extracting a larger share of the rent from reserved markets.

Next, I test if the effects are different by firm's productivity within the product market. I interact the firm's initial productivity with the indicator $UpDereserv$. Results are presented in Table 7. Firstly, heterogeneity in productivity implies that better performing suppliers expand production following a demand shock. In fact, the growth in output is driven by a small portion of these high-performance firms. I find substantial increase in markups and prices, mainly from more productive firms.[37] In this context, the reductions in prices and marginal costs were not large enough to mitigate the increase in prices from the demand shock.

The effects on prices and markups are also heterogeneous by productivity. I find productive firms increase their markups and prices relatively more when the market concentration increases. Hence, while output is reallocated to more productive firms in the upstream supplier market, this reallocation effect is weaker in concentrated markets. These results suggest that reducing a production bottleneck generates substantial efficiency gains through upstream linkages, and this effect is stronger in more competitive upstream markets.

5.3 Effects of market power - Downstream

I repeat the above analysis for downstream markets. Firstly, more concentrated downstream markets raise their markups in response to lower marginal costs from dereservation. This incomplete pass-through results in significantly lower quantity growth for concentrated downstream markets [38]. Accounting for the fall in prices reported in the previous section, these results suggest that marginal costs fell by around 8% due to dereservation, consistent with the observed price trends.

Next, I test if the effects are different by firm's productivity within the downstream markets. There is indeed evidence of reallocation in Table 9. Larger firms in more competitive markets increase their quantity more suggesting that the intermediate input distortions were indeed binding for these firms. However, in concentrated downstream markets, larger firms optimally choose to partially absorb cost reduction in their markups with no evidence of

[37] These results are consistent with the trade literature that finds exchange rate shocks tend to affect markups and not export volumes (see Berman et al., 2012).

[38] Event-study specification of these results in the appendix show that only less concentrated markets exhibited a decline in prices with no specific pre-trends prior to dereservation.

reallocation. Hence, welfare gains from removing production bottlenecks is higher when downstream markets are more competitive, arising from both higher output and reallocation effects. The intuition for this mechanism is as follows: because distortive policies tax firms within a layer heterogeneously, then it is reasonable to expect the related input taxes to fall heterogeneously on firms in downstream product markets. Imagine within each layer, there are firms with varying marginal products. An input tax that is imposed by distorting suppliers means that these firms have lower profit margins. Moreover, they might not have access to quality inputs or even quantity needed to grow. This means that their intermediate inputs are distorted, stifling their growth.

5.4 Additional Robustness Checks

In this section, I document a series of checks to checks the robustness of results.

Exposure measures - There is significant heterogeneity in the reported input usage at the firm-level within each product market. This can be attributed to the highly disaggregated nature of the product classification of ASI. Using the reported input usage at the firm -level rather than the product market aggregation used to calculate exposure as above, I find the above effects to be consistent using the firm-specific measure of downstream exposure as well. [39].Results are shown in the Appendix.

Additional Controls - I test the robustness of the results to controlling for a variety of additional characteristics including the nic3digit Industry x year dummies that controls for any changes that affect all product markets within the industry; State x year dummies to account for potential concentration of certain product markets in particular states that experience differential growth; initial age x year dummies and log of capital for differential growth rates in the firm-level regressions. Results are similar to baseline findings.

Product-level time trends - Another concern for the upstream and downstream markets is that the timing of exposure to dereservation policy coincides with different product-specific growth rates. While I do not find any product-level pre-trends, I implement another robustness checks whereby I include separate time-trends for every production. The results remain robust.

Dropping outliers - While the firm-level analysis excludes observations above the 97th percentile and below the 3rd percentile, there is still the concern that product markets might

[39]This in particularly concerning for analysis focusing on the outcome variables for downstream firms because the control group could potentially include firms that failed to report intermediate inputs from reserved sectors. The degree of bias is unclear and assuming all product markets suffer from the same degree of misreporting mitigates some of the concerns with the reporting problem. The fact that firms fail to report an input would suggest that they do not consider it to be an important input and hence, the bias should be small.

have outliers that are driving the results. That is, there are product markets with high concentration, close to 1, whose effects might by biasing my results. I test the robustness of my results by excluding product markets with concentration higher than 0.90. The results remain robust after eliminating the monopolized markets as well.

Alternate measures of firm performance - While this paper is interested in studying the reallocation effects by firm performance, the measure of productivity used in the baseline analysis is itself estimated and can be prone to measurement errors. In the appendix, I present results using alternate measures of firm performance including market shares which are directly observed. The assumption here is that more productive firms have larger (revenue-based) market shares. Evidence suggests that this assumption is reasonable in my case as more productive firms increase their market share once the capacity constraints are removed in the reserved markets. Results are presented in the appendix and are similar to the baseline findings. Secondly, I also use a measure of labor productivity (defined as log of real value added per employee) directly calculated from the balance-sheet data and find the results to be very close to the baseline results as well.

5.5 Mechanisms

Several mechanisms can generate the reallocation observed in the linked markets following liberalization. Imposing firm-size restrictions works similarly to an input tariff for downstream customers. Topalova and Khandelwal (2011) finds that access to intermediate inputs improved productivity following trade liberalization in India. I find that removing capacity constraints has similar effects for downstream customers. While individual firms can overcome lack of quality products by importing inputs from abroad, the existence of transport and local coordination costs suggest that a lack of locally available high-quality inputs is likely to hinder the ability of productive firms to grow. Relatedly, the upgrading of downstream producers is likely to generate pressure on local suppliers to improve quality, much like foreign direct investment may lead to productivity improvements among domestic suppliers (Kugler, 2006). Apart from more or better buyers and suppliers, liberalization might also lead to improved matching between suppliers and buyers and enable the larger, more productive upstream and downstream firms to expand. In addition, lower costs of vertical integration could incentivize more productive firms to enter linked markets, increasing their size. These results empirically corroborate the importance of production network on firm-size dispersion as illustrated in Bernard et al. (2018). Hence, size-distortionary policies in linked markets can explain some of the left-skewed firm - size distribution observed in developing countries.

Firm-level evidence of endogenously variable markups can be explained by a large class of models including imperfect competition a la Cournot where more productive firms have larger market shares and face lower demand elasticity (Atkeson and Burstein, 2008), linear demand system with horizontal differentiation where demand elasticity increases with prices (Melitz and Ottaviano, 2008) and monopolistic competition with non CES demand and variable elasticity of substitution (Dhingra and Morrow, 2016). The key feature in all these models is that demand elasticity varies with firm productivity, and therefore markups vary within a market. With a supply or demand shock, firms react by increasing their markup the higher their productivity. Here, when elasticities vary, market allocations reflect the distortions of imperfect competition. In an influential work, Arkolakis et al. (2012a,b) show richer models of firm heterogeneity and variable markups are needed for these micro-foundations to determine the welfare gains from trade. Recent work by Edmond et al. (2018) studies the welfare costs of markups using these heterogeneous markup models and points to potential for industrial policies to reduce these costs. The empirical results presented in this paper allow us to conclude that endogenous markups materially affect the impact of regulatory regime changes on productivity gains across the supply-chain. They amplify some shocks and attenuate others. Unlike a perfectly competitive model, shocks to industries and firms have different effects on aggregate output and productivity that depends on the market structure of linked markets.

A model that closely aligns with the propagation mechanisms identified in this paper is Baquee (2016). He presents a framework where changes in the mass of varieties in each industry through firm entry and exit can propagate both upstream and downstream. He uses monopolistic competition, free-entry and IO linkages via constant-elasticity-of-substitution (CES) production functions. He shows changing dynamics between intertwined industries that are sufficiently uncompetitive.

This paper is also consistent with the classic double-marginalization problem analyzed in Spengler (1950) and the subsequent literature that studies the effects of market structure on pass-through. In this strand of literature, the effective demand elasticity for upstream firms depends on downstream pass-through. Here, markups are strategic substitutes in the sense of Bulow et al. (1985): upstream firm raising its mark-up, which is equivalent to imposing a tax on the other firm, induces the downstream firm to absorb this increase and lower its markup. As average market power of firms in upstream market increases, they increase their prices and lower their quantity when downstream taxes decreases. This leads to an increase in the input price that is further shifted to consumers by firms at the downstream layer. Thus, consumers are likely to enjoy a smaller fraction of the welfare gains when linked firms are less competitive. The resulting overestimation would to be large if upstream or downstream market tend to be less competitive and for most cases if the demand curve is relatively inelastic.

6 Aggregate Productivity implications

In this section, I present the aggregate productivity implications of dereservation. The firm-level redistribution pf inputs from less- to more-productive firms identified in the last section points to allocative efficiency gains driving productivity growth. I verify these results at the product-level in this section. For the allocative efficiency result, I explore two measures of aggregate productivity growth from the literature. The first is a Melitz-style reallocation where the aggregate productivity is the sum of unweighted average productivity and covariance of market share and firm productivity. Second is a markup reallocation effect where aggregate productivity growth is stronger when inputs assigned to firms with higher social value (higher markups) would increase welfare in the economy.

6.1 Reduced misallocation in reserved markets

This subsection outlines some of the first evidence of misallocation resulting from a policy change. Following Equation 5, output misallocation is large, if the revenue productivities are dispersed such that reallocating the production across firms significantly increases aggregate gross output. In this economy, resources are allocated optimally when all firms face the same or no distortions in output, i.e. there is no dispersion in returns to factors. Fig 4 shows the distribution of TFPR before and after dereservation. I find a significant fall in coefficient of variation (CV) in TFPR within reserved product markets, driven by both an increase in the average productivity and a fall in standard deviation. The left tail of TFPR is less thicker post liberalization, consistent with reservation favoring the survival of inefficient plants. Results are presented in Table 10 from a diff-in-diff specification. The CV in TFPR falls by 6 percent in reserved markets and is robust to inclusion of state x year fixed effects and 3-digit industry x year fixed effects as well.

Next, I decompose the productivity growth to identify the magnitude of gains that can be attributed to reduced misallocation. Removing capacity constraints increases the industry's aggregate sales by allowing existing firms to expand and new firms to enter the market[40]. In the absence of within-firm productivity improvement or when the degree is relatively small, least productive firms within the market will incur a loss in market share and the revenue distribution of surviving firms will shift leftward especially at the left tail.

Generally, misallocation is measured as the distance between aggregate productivity and

[40]This result holds as long as $\epsilon > 1$ higher than one resulting in a smaller fall in aggregate price.

a counterfactual frontier (usually another more developed country). Instead of determining the frontier that requires additional assumptions, I estimate misallocation by comparing aggregate productivity before and after resources are reallocated due to the removal of size restrictions in India. Since a highly distorted establishment becomes more integral to industry productivity when its distortions are removed, the extent of misallocation depends on which establishments bear the greatest distortions. When the most productive establishments also bear the largest distortions, overall productivity gains associated with the removal of distortion is higher than if less productive establishments bear the same distortions. Hence, misallocation is the difference in weighted average of establishment-level productivities, where the scaling factors are market shares $S_{ie} = P_{ie}q_{ie}/P_iQ_i$, i.e. establishment's value added relative to the value added of the industry. The intuition for the weights is as follows: when the output distortion faced by the establishment increases relative to the average distortion in the industry, the establishment declines in size.

$$\Phi_i = \frac{TFP_{i,post}}{TFP_{i,pre}} = \frac{\sum_{e=1}^{N} A_{ie}S_{ie,post}}{\sum_{e=1}^{N} A_{ie}S_{ie,pre}}$$

The average misallocation in the reserved product markets falls by 45 percent [41] with a significant variation across markets suggesting that returns to dereservation depend on other factors [42]. To ensure these results are not solely driven by other factors, I conduct a series of tests. Firstly, both upstream and downstream firms are exposed to the dereservation but only through IO linkages. Hence, we would expect the gains in TFP to be significantly smaller. I find upstream TFP to increase by 24 percent and downstream TFP to increase by 21 percent, significantly less than the TFP growth observed in the dereserved product market. Secondly, because most of the dereservation happened post 2004, I compare changes in TFP before and after 2004 for reserved vs never reserved product markets and find a 20 percent greater fall in misallocation amongst reserved product markets. While these estimates are correlational, it provides a rough sense of the productivity gains from dereservation. In the next step, I aim to isolate the gains that are attributable to the dereservation itself using the difference-in-difference.

Finally, following Pavcnick (2002), I decompose the weighted productivity measure TFP for a market i in year t into two parts: the unweighted technical productivity measure $\bar{A}$ and the total covariance between a firm's share of the market output and its productivity:

[41] $TFP_{pre} = 0.51$ whereas $TFP_{post} = 0.74$ implying an increase in firms' TFP of 45 percent

[42] An advantage of this measure of misallocation is that it allows for changes in entry and exit of establishments by allowing $S_{ie} = 0$ in the periods of non-operation, thereby capturing effects of turnover on productivity as well.

$$TFP_{it} = \sum_{ie} S_{iet} A_{iet} = \bar{A_{it}} + \sum_{ie} (S_{iet} - \bar{i}_t)(A_{iet} - \bar{A}_{iet}) \qquad (9)$$

Productivity growth Φ_s is then given by:

$$\Phi_s = \Delta \bar{A_{st}} + \Delta \sum_{e} (S_{est} - \bar{S}_{st})(A_{est} - \bar{A}_{st})$$

The first term represents the contribution of within firm productivity improvements amongst incumbents (due to increase in scale, innovations, access to intermediate input etc.) and the selection effect with regards to both the survival of incumbents and entry of new firms while the second term captures the reallocation effects to the aggregate productivity gains[43]. To evaluate the magnitude of the reallocation effect, I compute the covariance at the product-level and find the covariance to increase by 10% when the product market is dereserved. I find a 3 percent increase in average productivity for the dereserved product markets. Hence, a large share (82 percent) of the TFP gains for dereserved markets comes from reallocation rather than the growth in mean productivity[44]. The relatively small average productivity growth is consistent with findings in Martin et.al (2017) and Tewari and Wilde (2018). These results emphasize the need to focus on reallocation effects rather than the average effects when studying the gains from alleviating distortionary policies.

6.2 Productivity effects on linked markets

Firm-level evidence in linked markets points to improved allocation as more productive firms expand. However, while markup dispersion decreases in reserved markets, it increases in both upstream and downstream markets post liberalization, consistent with firm-level evidence. These results suggest efficiency losses in concentrated linked markets due to elimination of reservation. In Table 12, I test these implications using the correlation of productivity and market shares from Equation 9. The correlation of market share and productivity increases in less concentrated markets while deteriorating in more concentrated upstream and downstream markets, reducing the aggregate productive gains from dereservation. A question then arises if this worsening allocation is large enough to mitigate all the gains from eliminating a bottleneck i.e. are we just shifting bottlenecks with no real gains? The next subsection attempts to answer this question.

[43] Selection effects include the gap in productivity between surviving and exiting plants, between entering and exiting plants and the gap between surviving and entering plants

[44] A critique of this approach is that TFP is a production concept and has nothing to do with the value of additional output associated with technical efficiency gains. The increase in 'reallocation' is associated with an increase in final demand alleviates this concern.

6.3 Aggregate Productive Growth

In this spirit of Basu and Fernald (2002) and Petrin and Levinsohn (2012), Aggregate productivity growth (APG) is the extra value of output going to final demand net of any extra primary input costs:

$$APG = \sum_e (\bar{D}_e \Delta lnY_e) - \sum_e \sum_{X=K,M,L} \bar{D}_e [\sum_k (\bar{s}_{X_e}) \Delta lnX_e]$$

where $D_e = y_e / \sum_e VA_e$ are Domar-weights with $\bar{D}_e$ is the average of plant e's value added share weights and $\bar{s}_{input_e}$ is the average input share. [45]. This measure captures the Domar-weighted changes in final demand, and hence reflects the welfare gains from dereservation. An advantage of this approach is that both output and the revenue shares can be calculated directly in the data, avoiding the need to estimate production function elasticities and productivity as in the previous section. Given the repeated-cross sectional nature of the data, I focus on measuring this object in each year using the establishment-level weights provided in the ASI survey.

Assuming fixed technology (i.e. constant input coefficients) and no distortions in the primary and intermediate input markets, I decompose the AGP as follows:

$$APG = \underbrace{(\bar{\mu} - 1) \sum_{e=1}^{E} D_e \sum_{X=K,M,L} [\sum_k (s_{X_e}) dlnX_e] +}_{\text{Average markup effect}}$$

$$\underbrace{\sum_{e=1}^{E} D_e (\mu_e - \bar{\mu}) \sum_{X=K,M,L} [\sum_k (s_{X_e}) dlnX_e] +}_{\text{Allocative efficiency gains}} \underbrace{\sum_{e=1}^{E} D_e dA_e}_{\text{Technical efficiency gains}} \tag{10}$$

where $\bar{\mu} = \sum_{e=1} D_e \mu_e$ and μ_e is the firm-specific markup. See Appendix A for a derivation of this decomposition. The intuition of this expression is as follows: suppose a firm has a higher-than-average markup. Then, relative to the social optimum, that firm produces even less output than does the average firm. Productivity increases even more if input use rises in this firm relative to the average firm. Higher average markup distorts the labor-leisure choice and leads to underproduction. When markets are perfectly competitive, these markup adjustment channels do not exist. However, there can still be reallocation effects if there are other distortions in the linked markets. For example, downstream customers could be facing intermediate input distortion whereas upstream suppliers face output distortions that

[45] The appropriate weight to trace out the final impact of the plant-level gain is the Domar weight, as an increase in intermediate input supply would lead to more output some of which may go directly to final demand and some go off to intermediate input consumption further downstream.

misallocate all their inputs. Because I observe changing markups and divergence of markups and quantity in more concentrated linked markets, I test these implications at the aggregate level using ΔAE:

$$\Delta AE \propto \Delta \sum_{e=1}^{E} D_e(\mu_e - \bar{\mu}) \sum_{Input=K,M,L} \sum_{k} (s_{input_e})(X_e - \bar{X})$$

where allocative efficiency from markup dispersion AE is the correlation of input shares and markups. APG grows by 18% in the reserved market. With a technical productivity growth of 3% in the previous section, 78% of the APG is a result of reduced markups and improved allocative efficiency. In Table 15, I present the results on APG in linked markets. In upstream markets, there is a substantial growth in APG that is attenuated by increased concentration. The significant growth in APG for upstream markets, much larger than the allocative efficiency gains suggests that demand shocks mainly operate by alleviating other input distortions and increasing technical productivity. However, in highly concentrated markets, the market-power induced efficiency loss outweighs the reallocation effects. The divergence in the covariance of markups and inputs can explain nearly all of the fall in APG from increasing concentration. In the downstream markets, there is no significant growth in APG within less concentrated markets despite a small improvement in allocative efficiency. From a social perspective, these high-markup firms were too small to begin with, and so the reallocation of factors towards them has improved allocative efficiency. A rough intuition for small but insignificant APG is that the resulting increase in average markup abates any gains in allocation. Within more concentrated markets, both APG and allocative efficiency worsens. Here, the reallocation was insufficient to overcome the losses from increasing markups and markup dispersion. Allocative inefficiency from markups can explain 56% of the fall in APG in downstream markets.

6.3.1 Aggregation

Results thus far provide estimates for the nature and intensity of propagation of deregulation through IO linkages. I conclude this section by using the above findings to obtain a back-of-the-envelope estimate of the overall productivity impact of dereservation and the role of linkages. I compute the *APG* under different scenarios using estimates from the previous sections weighted by sector-level Domar weights.

Recall that reserved sector accounted for 13 percent of GDP in India prior to dereservation. The reserved markets experienced (on average) a productivity growth of 18% following the removal of capacity constraints. Absent any propagation or amplification mechanism, dereservation can account for 0.13 x 0.18 = 0.023 percentage increase in aggregate productivity in the manufacturing sector. These results are consistent with the structural estimates of Garcia-Santana and Pijioan-Mas (2013) using data prior to dereservation and a Lucas span-of-control model. Nishida et al. (2016) estimates that average productivity growth was around 6.7% a year in India over the period studied in this paper, primarily driven by reallocation of intermediates. This observation suggests that the dereservation can account for 1/3 of the productivity growth in India around that period. However, it cannot account for the large gap in manufacturing TFP existing between the US and India.

Next, I sum the estimates for the average intensity of IO propagation weighted by the corresponding Domar weight of firms (18 percent for downstream and 35 percent of upstream). Taking these weights as a baseline and holding all else constant, I find that the direct and indirect propagation of the shock over IO linkages can account for a 3.77 percentage point growth in aggregate productivity. Propagation through IO linkages can account for roughly 65 percent of the aggregate gains with a significant fraction due to upstream propagation of the shock.

Aggregate Productivity Effects of linkages

	Upstream	Reserved	Downstream
	(1)	(2)	(3)
Ignoring IO linkages		2.34 %	
IO linkages with Low HHI	+ 1.35%		+ 0.05%
IO linkages with High HHI	- 0.69%		- 0.16%

In the final row, I subtract the efficiency losses that occurs within highly concentrated markets. There are also feedback effects through raising input costs and lower demand growth from incomplete-pass through that can mitigate the APG for reserved markets. Results are presented in Table 14. I find stronger backward propagation from downstream in line with previous evidence whereby increased customer concentration decreases APG for reserved markets.These estimates suggest with sufficiently competitive markets, IO linkages can amplify the gains from reducing distortions. Back-of-the-envelope calculations suggest that downstream HHI of 3390 ($\geq$ 90th percentile) and upstream HHI of 7500 ($\geq$ 95th percentile) in upstream wipe out all multiplier effects. As a final remark, I note that these effects are a lower bound for the real effects as I restrict my analysis to the immediate suppliers and customers of reserved markets. The intensity of propagation diminishes as the shock travels over the chain.

6.4 Discussion

Evidence of reduced misallocation and increased productivity in dereserved markets suggests that SSI reservation was indeed an important source of misallocation affecting a large share of manufacturing in India. Contrarily, Hsieh and Klenow (2009) found that misallocation in India worsened over the period from 1987 to 1994 during aother large reform episode that included trade liberalization and delicensing of the "raj" system. This puzzling evidence was further corroborated by Bollard, Klenow, and Sharma (2013) who found that although this period witnessed rapid productivity growth for their sample of very large firms, little of the productivity growth was due to changes in misallocation. They all conclude that APG was primarily driven by within-plant increases in technical efficiency and not between-plant reallocation of inputs.

Contrary to modelling that assumes size-distortions result in an increase in the equilibrium number of establishments, a decline in the average establishment size and concentration, I find the number of establishments increases post-reservation as larger multiproduct firms could enter the market and vertically integrate production. In fact, Tewari and Wilde (2018) find that multiproduct firms are the main entrants into newly de-reserved markets, increasing their product scope and productivity. This suggests that that structural modelling that ignores multiproduct establishments is misleading. Dereservation may have affected the optimal behavior of multiproduct establishments in linked markets, resulting in improved allocation. In addition, instead of an increase in concentration and decrease in competition, the dynamism from increased entry had the opposite effects.

Finally, my results suffer from limitations that can be addressed in future work. My data does not allow to identify the input-supplying firm, hence I do not observe whether matching between firms change. This would require a detailed firm-level transaction data but can offer insights on the channels of rellocation. Additionally, this study ignores the reallocation of resources across product markets as emphasized by Epifani and Gancia (2011). This could be a potential area of future study[46]. It would also be fruitful to study the interaction of trade and industrial policy in this context. For example, do exports grow in the dereserved markets? is there a change in imported input consumption? Finally, the analysis in this paper is partial equilibrium as I am not exploring the effects on higher order or horizontally related markets. I also abstract away from the entry and innovation effects from changing markups as well as labor market effects[47]. A dynamic general equilibrium framework that captures

[46] Existing literature points to substantially smaller reallocation effects across sectors relative to reallocation within sector. See Berman et. al (2012) for an exploration in the exchange rate pass-through context.

[47] I am only focusing on the static gains.This is a reasonable assumption given that I find no significant changes in the number of establishments within vertically linked markets over the medium-term.

the aggregate effects would require one to construct detailed product-level IO table as well as estimate parameters like the centrality of the affected market, elasticity of substitution and upstream and downstream markups. This could be an interesting avenue for future work especially if the estimate can provide a bound on the IO multiplier by market power.

7 Conclusion

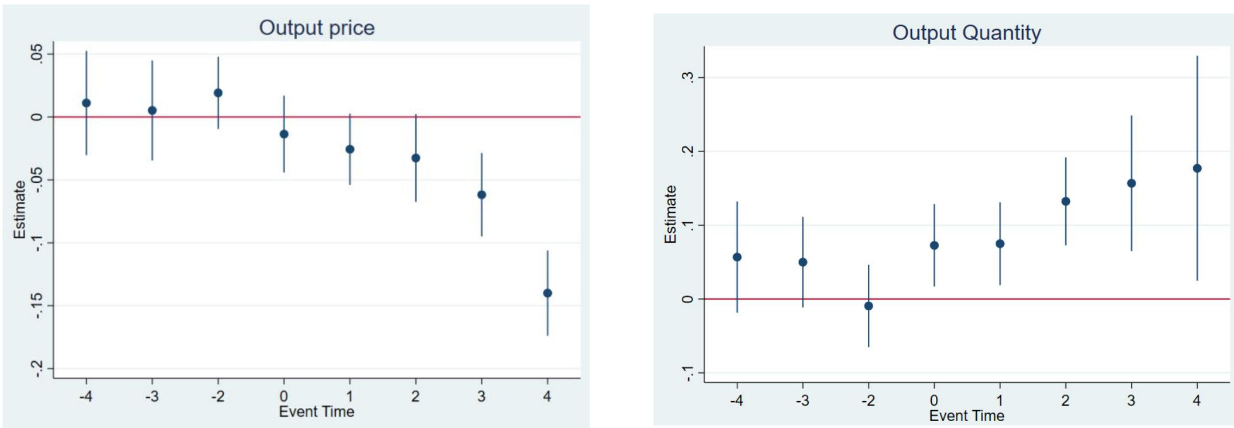
This paper studies the aggregate productivity effects of reducing size-distortionary polices that constrain larger and more productive firms. These types of policies are common across the world and have been shown to reduce productivity and output by increasing misallocation. My results showcase the importance of accounting for IO linkages when implementing selective reforms that affect a subset of markets. Leveraging a natural experiment in India, I show that eliminating size-restrictions in one market affects productive firms across the supply-chain. Consequently, piecemeal reforms have a much larger impact on the macroeconomy as it increases the aggregate productivity of not only directly exposed markets, but also of those that are connected to it. Nearly all of these productivity gains are driven by reallocation of inputs to more productive firms.

However, I find that response of the aggregate economy to reforms can be different depending on the micro-structure of the underlying network. I find that eliminating a size restriction propagates to upstream suppliers and downstream customers by triggering large reallocations of factors of production within competitive linked markets. However, when markets across the supply chain are concentrated, their efficiency worsens as inputs are reallocated to less productive firms with lower markups. Uncompetitive markets would become the new binding bottlenecks in the supply-chain due to increasing markups driven by larger and more productive firms.

My empirical results have nuanced consequences for policymakers. A government that ignores the fact that the upstream or downstream market is imperfectly competitive and thus ignores the resulting markup distortions, will make imprecise predictions concerning the gains from selective policy interventions. These results also underscore the role of IO linkages in shaping the overall market structure including the firm-size and markup distribution and demonstrates the possibility that a small industry can have an arbitrarily large effect on the economy.

Results

Figure 1: Effects on dereserved product markets



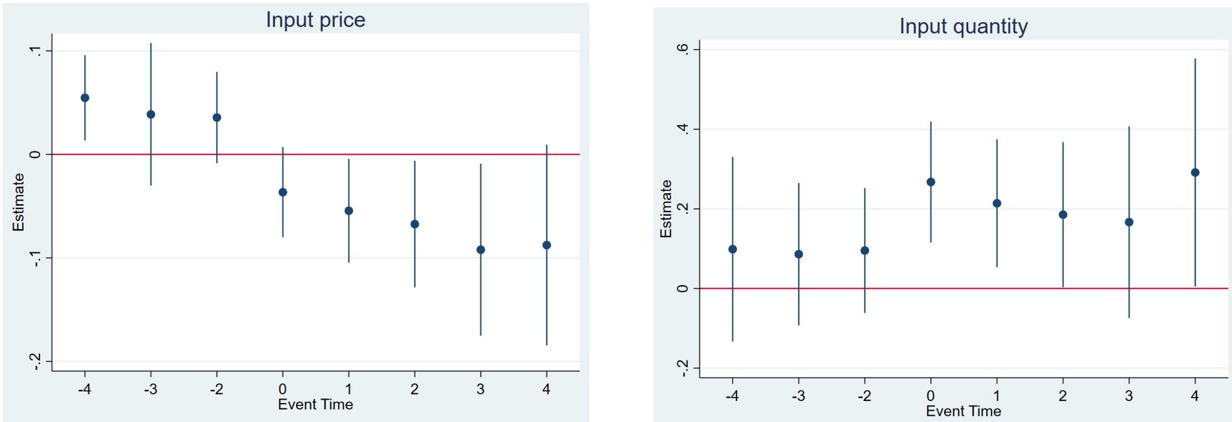
Note: The figures display the coefficients and 95 percent confidence intervals for the β_m coefficients in using the event-study regression specification (1). Output prices are at the firm-level while revenue is aggregated to the product-level. Outcome variables are logged and observations are trimmed above and below the 3rd and 97th percentiles for output prices within each market. I impose the normalization that $\beta_{-1} = 0$ and errors are clustered at the product -level.

Table 1: Impact of dereservation on product-level outcomes

	ln(revenue)	ln(quantity)	ln(labor)	ln(estab)
Dereserv	0.243**	0.329*	0.180*	0.201***
	(0.115)	(0.175)	(0.104)	(0.0549)
Product FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Products	4088	4088	4088	4088
Observations	22647	19591	22647	22647

Note: The table displays resuls from the product-level regressions using (2). *Dereserv* is a dummy variable that takes a value 1 when the product is removed from the list of reserved products. Regressions are weighted by the initial labor shares and errors are clustered at the product-level. $^{*}p < 0.10$, $^{**}p < 0.05$,$^{***}p < 0.01$

Figure 2: Effects on downstream inputs



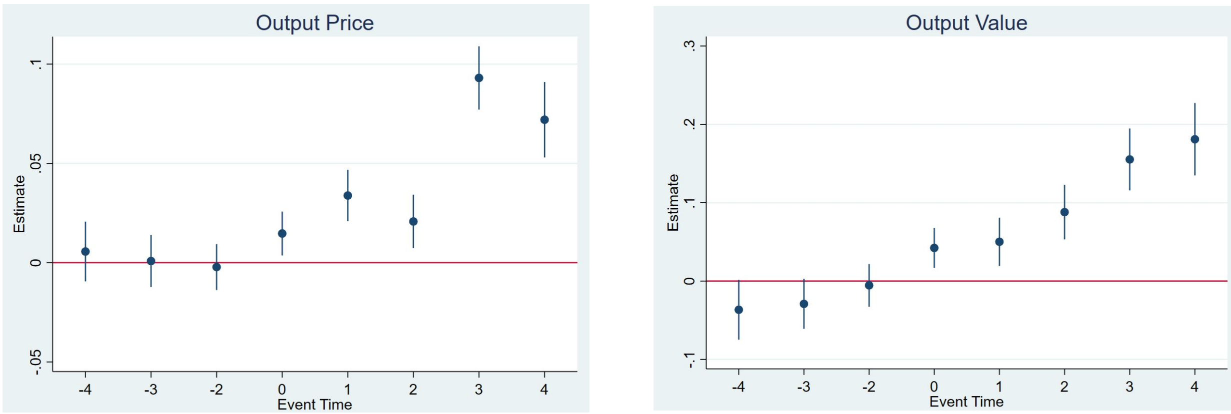
Note: The figures display the coefficients and 95 percent confidence intervals for the β_m coefficients in using the event-study regression specification (1). Here, regressions include firmxinput fixed effects and weighted in the inverse propensity score matching. I impose the normalization that $\beta_{-1} = 0$ and errors are clustered at the plant-level.

Table 2: Impact on downstream market by exposure

	(1)	(2)	(3)
	ln(revenue)	ln(price)	ln(quantity)
$DownDereserv * Exposure^{Down}$	0.0106***	-0.0331*	0.0428**
	(0.00235)	(0.017)	(0.0198)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Number of Clusters	94362	94434	94362
Observations	239893	240098	239893

Note: The table displays resuls from the firm-level regressions using (2). *DownDereserv* is a dummy variable that takes a value 1 when the first reserved input is removed from the list of reserved products. Regressions are weighted by the sampling multipliers from ASI and errors are clustered at the firm-level. $^*p < 0.10$, $^{**}p < 0.05$,$^{***}p < 0.01$

Figure 3: Effects on upstream customers



Note: The figures display the coefficients and 95 percent confidence intervals for the β_m coefficients in using the event-study regression specification (1). I impose the normalization that $\beta_{-1} = 0$ and errors are clustered at the plant-level.

Table 3: Impact on upstream market by exposure

	(1)	(2)	(3)
	ln(revenue)	ln(price)	ln(quantity)
$UpDereserv * Exposure^{Up}$	0.0571***	0.0167***	0.0447**
	(0.013)	(0.0054)	(0.013)
FirmxProduct FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Number of Clusters	3065	3065	3065
Observations	94788	94049	93948

Note: The table displays resuls from the firm-level regressions using (2). *UpDereserv* is a dummy variable that takes a value 1 when the first reserved output market is removed from the list of reserved products. Regressions are weighted by the sampling multipliers from ASI and errors are clustered at the firm - level. $^{*}p < 0.10$, $^{**}p < 0.05$,$^{***}p < 0.01$

Table 4: Impact on reserved markets by linked market concentration

	ln(revenue)	ln(quantity)	ln(labor)	ln(estab)
Dereserv	0.243**	0.329*	0.180*	0.201***
	(0.115)	(0.175)	(0.104)	(0.0549)
Dereserv*Upstream HHI	-0.0409**	-0.0252	-0.0285*	-0.0121**
	(0.0197)	(0.0325)	(0.0168)	(0.00555)
Dereserv*Downstream HHI	-0.0445	-0.0294	-0.000309	-0.00184
	(0.0198)	(0.0300)	(0.0171)	(0.00813)
Product FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Products	4088	4088	4088	4088
Observations	32704	32704	32704	32704

Note: Results from product-level regressions. *Dereserv* is a dummy that equals 1 when the reserved product market is dereserved and 0 otherwise. HHI is the concentration of the product market. Upstream HHI and Downstream HHI are measured as the weighted input shares of upstream products and weighted output sale share of downstream markets. Errors are clustered at the product-level. Standard error in parentheses.$^{*}p < 0.10$, $^{**}p < 0.05$,$^{***}p < 0.01$

Table 5: Marketshares of productive firms under dereservation

	(1)	(2)	(3)
	ln(marketshare)	ln(marketshare)	ln(marketshare)
$Productivity_{Pre} * Dereserv$	0.0905*	0.0809*	0.0787*
	(0.0504)	(0.0466)	(0.0450)
Dereserv	0.0416	0.0326	0.0180
	(0.0397)	(0.0409)	(0.0323)
Firm x Product FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm -level controls	No	Yes	Yes
IndustryxYear FE	No	No	Yes
State-specific Trend	No	No	Yes
Products	4288	4288	4288
Observations	201254	192694	192694

Note: Results from establishment-level regressions and restricted to incumbents. The dependent variable is (ln) marketshare of the firm. *Dereserv* is a dummy that equals 1 when the product market is dereserved and 0 otherwise. Productivity is demeaned. Column 2 includes firm-level controls - capital, age and labor while Column 3 includes the regional trends and industry (3-digit) level x year FE. Errors are robust clustered at the product- level. The regressions exclude outliers in the top and bottom 3rd percent of the productivity. All regressions include firm–product and year fixed effects. Standard error in parentheses.$^{*}p < 0.10$, $^{**}p < 0.05$,$^{***}p < 0.01$

Table 6: Upstream effects by concentration

	ln(price)	ln(price)	ln(output)	ln(output)
	Low HHI	*High HHI*	*Low HHI*	*High HHI*
UpDereserv	0.0119	0.0451**	0.0621*	0.0502**
	(0.00772)	(0.0196)	(0.0368)	(0.0183)
Firm x Product FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Products	2377	2743	2377	2743
Observations	152812	140929	152812	140929

Note: Results from establishment-level regressions and restricted to incumbents. *UpDereserv* is a dummy that equals 1 when the reserved product market that uses intermediate inputs from the upstream is dereserved and 0 otherwise. Errors are robust clustered at the product- level. The regressions exclude outliers in the top and bottom 3rd percent of the output price within a product x year. Standard error in parentheses.$^{*}p < 0.10$, $^{**}p < 0.05$,$^{***}p < 0.01$

Table 7: Upstream effects by productivity

	ln(price)	ln(price)	ln(markup)	ln(markup)	ln(output)	ln(output)
	Low HHI	*High HHI*	*Low HHI*	*High HHI*	*Low HHI*	*High HHI*
UpDereserv	0.0378***	0.0536**	0.0199***	0.0140	0.0114	0.0233 **
	(0.00888)	(0.00905)	(0.00646)	(0.0169)	(0.0156)	(0.00853)
UpDereserv*Productivity	0.00721	0.0158***	0.0211***	0.0569***	0.128***	0.0836**
	(0.00684)	(0.00603)	(0.00765)	(0.00462)	(0.0207)	(0.0271)
Firm x Product FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	174354	193200	174354	193200	174354	193200

Note: Results from establishment-level regressions and restricted to incumbents. *UpDereserv* is a dummy that equals 1 when the reserved product market that uses intermediate inputs from the upstream is dereserved and 0 otherwise. Productivity is standardized. Regressions are split median HHI. by the Errors are robust clustered at the firm - level. The regressions exclude outliers in the top and bottom 3rd percent of markups. Standard error in parentheses.$^{*}p < 0.10$, $^{**}p < 0.05$,$^{***}p < 0.01$

Table 8: Downstream effects by concentration

	(1)	(2)	(3)	(4)
	ln(markup)	ln(markup)	ln(output)	ln(output)
	Low hhi	*High hhi*	*Low hhi*	*High hhi*
DownDereserv	0.0151	0.0460*	0.0930*	0.0492**
	(0.0318)	(0.0250)	(0.0267)	(0.0188)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Number of Clusters	2316	2839	2316	2839
Observations	82868	105709	82868	105709

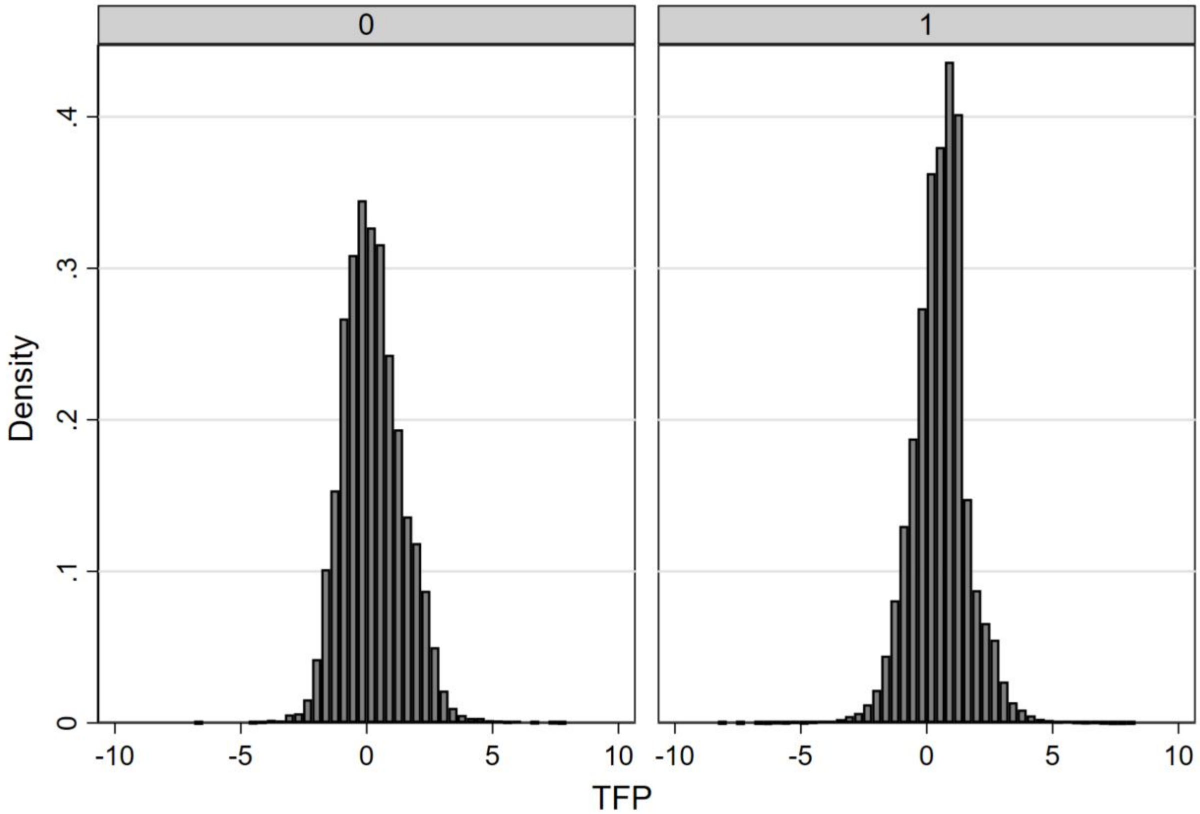
Note: Results from establishment-level regressions and restricted to incumbents. *DownDereserv* is a dummy that equals 1 when the intermediate input market is dereserved and 0 otherwise. Errors are robust clustered at the firm- level. The regressions exclude outliers in the top and bottom 3rd percent of the markups within a product x year. Standard error in parentheses.$^{*}p < 0.10$, $^{**}p < 0.05$,$^{***}p < 0.01$

Table 9: Downstream effects by productivity

	ln(price)	ln(price)	ln(markup)	ln(markup)	ln(output)	ln(output)
	Low HHI	*High HHI*	*Low HHI*	*High HHI*	*Low HHI*	*High HHI*
DownDereserv	-0.0281***	-0.0118	-0.0185	0.00615	0.0419***	0.0385**
	(0.00838)	(0.0126)	(0.0115)	(0.0137)	(0.0155)	(0.0110)
DownDereserv*Productivity	0.0141**	-0.0139	0.0303***	0.120***	0.0671**	-0.0179
	(0.00702)	(0.0102)	(0.0112)	(0.0225)	(0.0291)	(0.0252)
Firm x Product FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	165855	170894	165855	170894	165855	170894

Note: Results from establishment-level regressions and restricted to incumbents. *DownDereserv* is a dummy that equals 1 when the intermediate input market is dereserved and 0 otherwise. Errors are robust clustered at the firm- level. The regressions exclude outliers in the top and bottom 3rd percent of the markups within each year-product market. Standard error in parentheses.$^{*}p < 0.10$, $^{**}p < 0.05$,$^{***}p < 0.01$

Figure 4: TFPR Histogram for reserved market



Note: The figures display the distribution of firm-level TFPR within reserved markets weighted by the sampling multipliers where 0 is the distribution prior dereservation and 1 is following the dereservation

Table 10: TFPR variation in reserved market

	(1)	(2)	(3)
	TFPR dispersion	TFPR dispersion	TFPR dispersion
Dereserv	-0.0523**	-0.0638*	-0.0424*
	(0.0284)	(0.0364)	(0.0238)
State x year FE	No	Yes	Yes
Industry x year FE	No	No	Yes
Number of Clusters	4727	4727	4727
Observations	27295	27295	27295

Note: The table reports the effect of dereservation on the CV of TFPR. *Dereserv* is a dummy that equals 1 when the product market is dereserved. Regressions are at the product-level and weighted by the initial labor shares. Firm-level TFPR is trimmed above and below the 3rd and 97th percentiles before calculating the variation. All regressions include Year and Product level FE. Errors are clustered at the product-level.

Table 11: Decomposition of TFP for reserved market

	(1) tfp	(2) correlation	(3) meanproductivity
Dereservation	0.132**	0.0974***	0.0330***
	(0.0525)	(0.0305)	(0.00489)
Observations	29250	29250	29250
Year FE	Yes	Yes	Yes
Product FE	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Regression is at the product-level. *Dereserv* is a dummy that equals 1 when the product market is dereserved and 0 otherwise. All regressions include product and year fixed effects. Regressions are weighted by the initial labor share and errors are robust clustered at the product level. Standard error in parentheses.$^{*}p < 0.10$, $^{**}p < 0.05$,$^{***}p < 0.01$

Table 12: Reallocation effects in linked markets

	Correlation *Low HHI*	Correlation *High HHI*	Correlation *Low HHI*	Correlation *High HHI*
$UpDereserv * Exposure^{Up}$	0.0104*	-0.103***		
	(0.00560)	(0.0153)		
$DownDereserv * Exposure^{Down}$			0.00533***	-0.107***
			(0.00168)	(0.00425)
Observations	14627	24164	14877	24547

Note: Results from product-level regressions. Dependent variable is the $Corr(productivity, marketshare)$ from Equation 4. *Exposure* is standardized. Regressions are weighted by the initial labor shares and errors are robust clustered at the product- level. Standard error in parentheses.$^{*}p < 0.10$, $^{**}p < 0.05$,$^{***}p < 0.01$

Table 13: Aggregate productivity growth within reserved market

	APG_i	APG_i	APG_i
Dereserved	18.8**	19.9**	16.4**
	(4.55)	(4.75)	(4.73)
Products	4046	4046	4046
Product controls	No	Yes	Yes
Industry x Year FE	No	No	Yes

Note: Results from product-level regressions. Dependent variable is APG_i within a market inflated by the sampling weights from the ASI. *Dereserv* is a dummy that equals 1 when the reserved product market is dereserved and 0 otherwise. HHI is the concentration of the product market. UpstreamHHI and DownstreamHHI are measured the weighted input shares of upstream products and weighted output sale share of downstream markets. Regressions are weighted by the initial labor shares and errors are robust clustered at the product-level. Standard error in parentheses.$^{*}p < 0.10$, $^{**}p < 0.05$,$^{***}p < 0.01$

Table 14: APG in reserved markets by market concentration

	APG_i	APG_i	APG_i	APG_i
Dereserv	18.82***	20.50**	18.23***	18.26***
	(4.55)	(6.83)	(4.11)	(4.11)
Dereserv*HHI		-4.46***		
		(1.72)		
Dereserv*Upstream HHI			-2.27*	
			(1.19)	
Dereserv*Downstream HHI				-8.81*
				(4.73)
Products	3957	3957	3957	3957

Note: Results from product-level regressions. Dependent variable is APG_i within a market inflated by the sampling weights from the ASI. *Dereserv* is a dummy that equals 1 when the reserved product market is dereserved and 0 otherwise. HHI is the concentration of the product market. UpstreamHHI and DownstreamHHI are measured the weighted input shares of upstream products and weighted output sale share of downstream markets. Regressions are weighted by the initial labor shares and errors are robust clustered at the product-level Standard error in parentheses.$^{*}p < 0.10$, $^{**}p < 0.05$,$^{***}p < 0.01$

Table 15: APG in linked markets

	Low HHI APG_i	*High HHI* APG_i	*Low HHI* APG_i	*High HHI* APG_i
$UpDereserv * Exposure^{Up}$	7.284**	3.821**		
	(3.305)	(1.738)		
$DownDereserv * Exposure^{Down}$			1.295	-2.243***
			(0.843)	(0.504)
	Allo. Efficiency	Allo. Efficiency	Allo. Efficiency	Allo. Efficiency
$UpDereserv * Exposure^{Up}$	1.619*	-2.378*		
	(0.835)	(0.758)		
$DownDereserv * Exposure^{Down}$			0.698***	-0.572**
			(0.423)	(0.264)
Products	2665	2716	2665	2716
Product controls	Yes	Yes	Yes	Yes
Industry x Year FE	Yes	Yes	Yes	Yes

Note: Results from product-level regressions. Dependent variable is sum of VA_{ie} within a market inflated by the sampling weights from the ASI. Regressions are weighted by the initial labor shares and errors are robust clustered at the three-digit level to allow for arbitrary error correlations within larger industries over time. Standard error in parentheses.$^{*}p < 0.10$, $^{**}p < 0.05$,$^{***}p < 0.01$

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Appendix A: Proof for Aggregate Productivity Growth measure

In this section, I provide the derivation for Equation 10 that decomposes the aggregate productivity growth measure. Assume each firm e has a production function for gross output given by:

$$Y_e = F^e(K_e, L_e, M_e, Z_e)$$

where K_e is the capital, L_e is labor, M_e is the intermediate inputs and Z_e is firm-specific productivity. This production function encompasses the cobb-douglas production from Equation 1. I assume constant-returns-to-scale with firms having market power in the output market but no monopsony power. Furthermore, I assume that each establishment uses materials in fixed proportions to output, i.e. there is no technological change. In addition, there are no factor market frictions and any wedge arises from variable markups. First, rewriting the output growth in terms of input growth and technology [48]:

$$dy_e = \frac{F^e_L L_e}{F^e} dl_e + \frac{F^e_K K_e}{F^e} dk_e + \frac{F^e_M M_e}{F^e} dm_e + \frac{F^e_Z Z_e}{Z^e} dz_e$$

First order condition of cost-minimization implies for any input J:

$$\frac{F^e_J J_e}{F^e} = \mu_e s_{Je}$$

noindent where input share in nominal gross output is given by $s_{Je} = \frac{P_J X_J}{PQ}$ and μ_e is the firm-specific markup. Then, it follows that

$$dy_e = \mu_e[s_{L_e} dl_e + s_{K_e} dk_e + s_{M_e} dm_e] + \frac{F^e_Z Z_e}{Z^e} dz_e$$

$$dy_e = \mu_e dx_e + (1 - \mu_e s_{M_e}) dz_e$$

Then, substituting the above equation to the definition of aggregate productivity:

$$APG = \sum_{e=1}^{E} D_e(\mu_e - 1) dx_e + \sum_{e=1}^{E} D_e(1 - \mu_e s_{M_e}) dz_e$$

where D_e is the firm's share of nominal value added. Decomposing the equation further to capture allocative efficiency:

[48]See Basu and Fernald (2002) for an explanation on how this productivity growth measure is proportional to welfare gains

$$APG = (\bar{\mu} - 1)\sum_{e=1}^{E} D_e dx_e + \sum_{e=1}^{E} D_e(\mu_e - \bar{\mu})dx_e + \sum_{e=1}^{E} D_e(1 - \mu_e s_{M_e})dz_e$$

where $\bar{\mu} = \sum_{e=1}^{E} D_e \mu_e$. As discussed in Hulten (1978), if all firms were perfectly competitive, only the last term of technical efficiency changes matter. The second term, markup-reallocation term, represents shifts of inputs toward uses with higher social valuations, i.e. reallocating inputs from low- to high-markup firms shifts resources towards uses where consumers value them more highly. If there is correlation between market power and firm's inputs, then imperfect competition affects aggregate productivity even if the average markup is small. Finally, if average markup is greater than one, then the markups distort labor-leisure choice. Consumers would prefer to provide more capital and labor and consume the extra goods they could produce, since the utility value of these goods exceeds the disutility of producing them. Note that the final term can be decomposed further like Pavnick (2002) with an average technical efficiency measure and a correlation term. There are two diffrences though: first, the weights are based on firm's share of value added instead of revenue share. Hence, firms that use relatively more intermediate inputs will have smaller weights now. Secondly, there is an additional term on the weights $1 - \mu_e s_{M_e}$ that results in lower weights for productive firms that charge higher markups and/or have a large share of intermediate inputs. Finally, I ignore the distortions in input markets in the above proof because of my focus on the role of markup distortions. Given that APG that is larger than can be explained markup reallocation alone, this suggests reduction in primary input distortions from demand/supply shocks where input distortion term R_x is given by:

$$R_x = (\bar{\mu_e} - 1)\sum_{e=1}^{E} D_e s_{X_e} \frac{P_{xe} - P_x}{P_x} dx_e$$

Here, aggregate productivity increases when inputs are reallocated to firms with higher marginal products.

Appendix B: Data Cleaning

I drop firm observations that do not report any labor, inputs or outputs in a given year. Second, I also drop establishments that report less than 4 employees with the idea that these are self-employed businesses. Next, I exclude extreme outliers in terms of key production variables such as revenue, employment, and input use. To calculate labor share, material share and capital share for each product within a multiproduct firm, I use the revenue share of the product. For firms that report multiple price for the narrow product category within a year, I take the average. I treat each observation as a firm with the caveat that there is a small possibility that it is part of a multi-unit firm. Capital is measured at the average of the starting and ending value within a given year. Material inputs include expenditures on fuel and electricity. Labor includes temporary contract workers. All aggregated material input costs are deflated using the IO table weighted nic2digit input index. Wages are delfated with GDP deflator and Capital is deflated with capital cost deflator. All product and industry codes are in the ASICC - 04 and NIC - 04 classification respectively using concordance tables provided by the Central Statistics office.

Misreporting in prices - Even though there is supposed to be consistency in the unit of measurement of a narrowly defined 5-digit product, firms use other units while reporting that leads to abnormally high or small price values. For example, some firms might report price of milk in liters even though the questionnaire asks for kiloliters. To address this discrepancy, I initiate an algorithm based on Agarwal(2016) that addresses the misreporting as follows: 1) For each product in a given year, I drop the values that are smaller than 3rd percentile and larger than 97th percentile. 2) For each firm with at least 2 observations in product x prices, I drop firms whose prices exhibit a 10 fold increase. 3) I rank the prices of each product in a given year and calculate the difference. If the difference between two price observations is higher than 20x, I split the observations into two different product categories. Results are robust to alternate cutoffs.

Appendix C: Model of Variable Markups

In the section, I present a model that can explain the observed distributional effects in this paper. Within each market, a finite number of heterogeneous firms are engaged in imperfect competition with variable markups and input costs à la Atkeson and Burstein (2008). It includes a generalized version of quantity competition in which firms do not fully pass-through changes in their marginal costs to their prices because their optimal markup depends on their market share. Here, I am assuming production functions and consumer preferences are Cobb-Douglas in line with the benchmark model in this literature.

Firms play a static game of quantity competition. Specifically, each firm $e = 1, ..., E$ chooses its quantity q_{ie} sold in market i taking as given the cost of intermediate inputs from upstream market j, final consumption price p and quantity Q of the final product and a size-dependent distortions [49]. Note that under this assumption, each firm does take into account the fact that it has market power and that market price index P_i and quantities Q_i vary when that firm changes its quantity q_{ie} where:

$$Q_i = (\sum_{e=1}^{E} q_{ie}^{\frac{\sigma_i - 1}{\sigma_i}})^{\frac{\sigma_i}{\sigma_i - 1}}$$

$$P_i = (\sum_{e=1}^{E} P_{ie}^{1-\sigma_i})^{\frac{1}{1-\sigma_i}}$$

Given these preferences, each firm faces the demand curve $q_{ie} = P_{ie}{}^{-\sigma_i} P_i^{\sigma_i - 1} Q_i$.

With cournot competition, Atkeson and Burstein (2008) implies the following:

$$\mu_{ie} = \frac{\epsilon(s_{ie})}{\epsilon(s_{ie}) - 1} = \frac{\sigma_i}{\sigma_i - 1} \frac{1}{1 - s_{ie}}$$

where $s_{ie} = \frac{p_{ie} q_{ie}}{P_i Q_i}$ is the market share of the firm and $\epsilon_{ie} > 1$ is the subjective demand elasticity [50]. In this framework, demand elasticities vary with quantity and firms vary in productivity leading to resource allocation across different types of firms and variable markups within the market. The important take-away from this is that more productive firms will produce higher quantity but also charge higher markups as a larger share of market's revenue s_{ie} implies lower demand elasticity [51].

[49] Most of the size-dependent distortions are on either capital or labor. To simply the model, here I am assuming that a unit of output q requires a unit of capital or labor that is constant and varies with firm productivity. Hence, a tax of capital or labor can be throught of as a tax on output.

[50] The subjective demand elasticity is the weighted average of the elasticity of substitution across varieties σ_i and the elasticity of substitution across sector which is here equal to one.

[51] This implication that inverse demand elasticity is increasing with quantity is common in the literature using other models as well (see Mrazova and Neary (2013) and Krugman (1979) for example.)

Proposition 1: *Market share s_{ie} captures the market power of firm within a market in terms of its ability to charge a markup*

The intuition as follows: Large firms have a higher market share and thus they can use this higher market power to charge even higher markups, which in turn aggregate to a higher industry-level markup. Then, pass-through elasticity is given by:

$$\frac{\partial p_{de}}{\partial p_r}\frac{p_r}{p_{de}} = \underbrace{(\frac{\sigma_d(1-s_{de})+s_{de})}{\sigma_d})}_{\text{markup adjustment}} \underbrace{(\gamma_{ie}\omega_{rd})}_{\text{marginal cost share of input}}$$

Then, when there is an uniform input-cost shock such that $p_r \to 0$:

$$\frac{\partial \mu_{de}}{\partial p_r} < 0 \text{ and } \frac{\partial \mu_{ue}^2}{\partial p_r \partial s_{ue}} > 0$$

Following an input cost decrease, markups increase and firms with larger market share increase their markups more leading to higher average markup and markup dispersion.This heterogeneous response to input cost shocks would then logically generate a heterogeneous quantity response whereby quantity dispersion falls. While the framework presented in this paper relies on the strong Cobb-Douglas or the constant elasticity-of-substitution functional assumptions commonly imposed in the literature, these results are not unique to the model presented here. A monopolistic competitive framework as in Krugman would yield similar results albeit through a different mechanism as well as complex variable elasticity of subsitution models (Arkolakis et al., 2015; Dhingra and Morrow, 2012).

Appendix D: Production function estimation

I use the "supply-side" approach based on Hall(1986), De Loecker and Warzynski(2012) and De Loecker et al.(2016) to calculate markups. The main advantage of this methodology is that it does not commit to a particular demand or market structure but adopt an empirical specification that nests the main models used in trade and industrial organization, including those that generate variable markups. Hence, it captures the reallocation effects as well as changes in residual demand and costs on markups. Apart from cost minimization, this method assumes that input adjustment is costless and that firms in the same industry face exogeneous input prices. Let Y_{it} be the deflated firm-level sales. I use a flexible translog, gross-output production function whereby the coefficients are the same across firms within an industry but the output elasticities, and consequently markups, vary by plant and by year within an industry. Taking logs of the gross output, translog production function:

$$y_{it} = \beta_l l_{it} + \beta_{ll} l_{it}^2 + \beta_k k l_{it} + \beta_{kk} k_{it}^2 + \beta_x x_{it} + \beta_{xx} x_{it}^2 + \beta_{lk} l_{it} k_{it} + \beta_{lx} l_{it} x_{it} + \beta_{kx} k_{it} x_{it} + \beta_{lkx} l_{it} k_{it} x_{it} + z_{it} + \epsilon_{it}$$

where z_{it} is firm's quantity - productivity TFP at time t and ϵ_{it} the measurement error. I follow the literature and control for the simultaneity and selection bias, inherently present in the estimation of the above equation [52]. I rely on a control function approach, paired with an AR(1) process for productivity to estimate the output elasticity of the inputs [53]. The resulting product-firm-year variation in markup is driven by both changes in plant-level revenue share for the variable input and changes in the mix of inputs used for production. The coefficients are estimated for each 2-digit industry separately. Importantly, I use control function to control for input prices of materials as in Deloecker et al. (2016). I incorporate dummies for firms around the capital cutoff as well as dummy for reserved status as state variables to the firms' production decisions. This allows firms that are not SSI or reserved to have different production technology. These dummy variables are used in the first step of the production function estimation. Given the large share of multiproduct firms, I also control for probability of being multiproduct and follow the approach in Deloecker et al. (2016) to allocate input shares to the respective products. The derived estimates are quantitatively similar to estimates from Deloecker et al. (2016) who uses the Prowess Public firm-level data from India.

[52] Simulatenity bias arises for example if productivity decrease leads to decrease in production inputs. Conversely, if an establishment's factor productivity increases, it will lead to increase in the used inputs over the same period.

[53] Fixed effects method resolves the problem of simultaneousness by fixing in the panel sample the error term in the observed time interval, whereas the instrumental variables method avoids the correlation between productivity and input choices.

Table D.1: Average Output elasticities, By Sector

Sector	Labor	Capital	Material	Returns to Scale
15 Food products and beverages	0.18	0.10	0.74	0.97
17 Textiles	0.093	0.091	0.79	1.00
18 Wearing apparel	0.10	0.098	0.81	1.03
21 Paper and paper products	0.18	0.056	0.79	1.02
23 Coke, refined petroleum products	0.038	0.12	0.87	1.02
24 Chemicals	0.20	0.10	0.70	0.99
25 Rubber and Plastic	0.10	0.13	0.84	1.06
26 Non-metallic mineral products	0.47	0.09	0.48	1.04
27 Basic metal	0.06	0.09	0.83	0.98
28 Fabricated metal products	0.15	0.083	0.77	1.04
29 Machinery equipment	0.24	0.036	0.80	0.98
31 Electrical machinery	0.20	0.091	0.75	1.05
34 Motorvehicles	0.16	0.097	0.76	1.07
Total	0.21	0.094	0.72	1.00

Note: The table reports the average output elasticities by sector with respect to each factor of production for the translog production function for all firms for the sample 2000 - 2013. The last column report the returns to scale which is the just of the output elasticities. Observations are trimmed above and below the 3rd and 97th percentiles for returns to scale within each sector.

Table D.2: Markups, By Sector

Sector	Mean	Median
15 Food products and beverages	1.37	1.06
17 Textiles	1.99	1.54
18 Wearing apparel	2.35	1.81
21 Paper and paper products	1.32	1.06
23 Coke, refined petroleum products	2.15	1.74
24 Chemicals	1.71	1.12
25 Rubber and Plastic	1.50	1.15
26 Non-metallic mineral products	2.14	1.55
27 Basic metal	1.76	1.20
28 Fabricated metal products	1.72	1.20
29 Machinery equipment	1.57	1.17
31 Electrical machinery	1.60	1.13
34 Motorvehicles	1.86	1.34
Total	1.69	1.21

Note: The table reports the mean and median markups by sector for the sample 2000 - 2013. Observations are trimmed above and below the 3rd and 97th percentiles for markups within each sector.

Table D.3: Markups and marginal costs of IO linked markets

	(1)	(2)
	log (marginal cost)	log (markup)
Outputshock	0.0310	0.0211***
	(0.0392)	(0.00796)
Inputshock	-0.0601**	-0.00508
	(0.0294)	(0.00328)
Number of Clusters	2232	2232
Observations	31049	31049

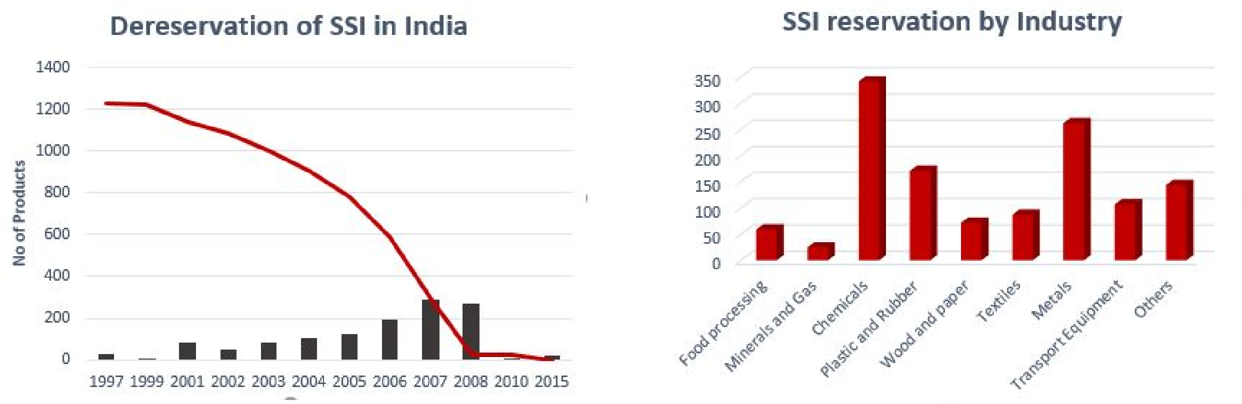
Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The table displays resuls from the firm-level regressions using (2). *UpDereserv* is a dummy variable that takes a value 1 when the first reserved output market is removed from the list of reserved products. Regressions are weighted by the sampling multipliers from ASI and errors are clustered at the product - level. $^{*}p < 0.10$, $^{**}p < 0.05$,$^{***}p < 0.01$

Appendix E: Additional Tables

Figure E.1: Dereservation Policy



Note: The figures displays the timeline of De-reservation and the variation in reserved products across industries in India. A total of 1256 products were reserved for SSI before 1997.

Table E.2: Pairwise Correlation Matrix across firm performance variables

	Productivity	Marketshare	Marginal Costs	Markups	Prices
Productivity	1.00				
Marketshare	0.16	1.00			
Marginal Costs	-0.33	-0.12	1.00		
Markups	0.12	0.070	-0.22	1.00	
Prices	0.036	0.095	0.97	0.070	1.00

Note: The table reports the pairwise correlation across the following firm performance variables: productivity, marketshare, marginal costs, markups and prices. All variables are expressed in logs. Markups, prices and marginal costs vary at the firm-product level, marketshare and productivity vary at the firm-level. Observations are trimmed above and below the 3rd and 97th percentiles for output prices within each sector.

Table E.5: HHI, By Sector

Sector	Mean	Median
15 Food products and beverages	6.54	1.42
17 Textiles	11.16	3.67
18 Wearing apparel	6.77	1.37
21 Paper and paperr products	11.19	2.63
23 Coke, refined petroleum products	17.15	7.13
24 Chemicals	18.21	6.56
25 Rubber and Plastic	14.16	4.53
26 Non-metallic mineral products	9.27	1.95
27 Basic metal	13.90	4.99
28 Fabricated metal products	15.77	6.25
29 Machinery equipment	16.94	8.06
31 Electrical machinery	13.50	4.09
34 Motorvehicles	17.06	5.83
Total	12.55	3.69

Note: This table presents the average and median HHI for a product market within each industry.

Table E.6: Market share and HHI

Sector	Mean	Median
Inv HHI at 5 digit	6.54	1.42
Market share	0.044	0.0025
Mean highest share	0.21	0.17
75th p.c. share	0.018	
95th p.c. share	0.125	
99th p.c. share	0.328	

Note: This table presents some summary statistics on the market share distribution for the whole sample

Table E.7: Upstream effects by market share

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(price)	ln(output)	ln(price)	ln(output)	ln(price)	ln(output)
	All firms	*All firms*	*Low HHI*	*Low HHI*	*High HHI*	*High HHI*
UpDereserv	0.0193***	0.0538	0.0119	0.0353	0.0478*	0.0798**
	(0.00718)	(0.0343)	(0.00960)	(0.0465)	(0.00250)	(0.0315)
UpDereserv*Mrktshare	0.00206	0.0420***	0.00687	0.0577***	0.00664	0.0353***
	(0.00287)	(0.00708)	(0.00466)	(0.0125)	(0.00472)	(0.00973)
Firm x Product FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Clusters	5010	5010	4071	4071	4300	4300
Observations	180324	181974	100833	92415	79491	89559

Note: Results from establishment-level regressions and restricted to incumbents. *UpDereserv* is a dummy that equals 1 when the reserved product market that uses intermediate inputs from the upstream is dereserved and 0 otherwise. Marketshare is standardized. Errors are robust clustered at the product- level. The regressions exclude outliers in the top and bottom 3rd percent of the productivity. Standard error in parentheses.$^{*}p < 0.10$, $^{**}p < 0.05$,$^{***}p < 0.01$

Table E.8: Downstream effects by marketshare

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(markup)	ln(output)	ln(markup)	ln(output)	ln(markup)	ln(output)
	All firms	*All firms*	*Low HHI*	*Low HHI*	*High HHI*	*High HHI*
DownDereserv	-0.00407	0.0467***	0.0104	0.0479***	-0.00898	0.0327**
	(-0.64)	(4.83)	(0.92)	(3.00)	(-0.94)	(2.26)
DownDereserv*Mrktshare	0.00558	0.00589	0.01016	0.1057***	0.00931*	0.00361
	(1.52)	(1.37)	(0.48)	(3.39)	(1.70)	(0.84)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Clusters	44331	52791	23413	28695	26210	31398
Observations	118032	150014	48775	60140	51421	64496

Note: Results from establishment-level regressions and restricted to incumbents. *DownDereserv* is a dummy that equals 1 when the intermediate input market is dereserved and 0 otherwise. Errors are robust clustered at the firm- level. The regressions exclude outliers in the top and bottom 3rd percent of the markups within each year-product market. Standard error in parentheses.$^{*}p < 0.10$, $^{**}p < 0.05$,$^{***}p < 0.01$

Effects on firm entry and competition

My analysis assumes static gains i.e. there is no substantial entry. Looking at the total number of establishments within a product market, I do not find significant changes either in the upstream or downstream but dereserved markets witness an increase in the number of establishments. The change in establishments both capture the exit of firms and entry of new firms. It is possible that for the upstream and downstream, while there was no net entry, there was some exit and entry. To rule out this, I look at the entry rate of firms. I again find no evidence of increased entry except for the dereserved markets itself. These results lend credibility to my assumption of fixed competitive structure in the linked markets.

Table A.9: Impact of dereservation on firm turnover

	(1)	(2)	(3)
	ln(estab)	ln(estab)	ln(estab)
UpDereserv	0.0134		
	(0.0199)		
Dereserv		0.0868**	
		(0.0383)	
DownDereserv			-0.0118
			(0.0140)
	ln(entryrate)	ln(entryrate)	ln(entryrate
UpDereserv	0.0102		
	(0.0100)		
Dereserv		0.0806**	
		(0.0382)	
DownDereserv			0.00626
			(0.00826)
Products	4368	4368	4368
Observations	27683	27683	27683

Note: Results from product-level regressions. The dependent variable $ln(estab)$ is the total number of establishments making a product. *Dereserv* is a dummy variable that takes a value 1 when the product is removed from the list of reserved products. *DownDereserv* is a dummy that equals 1 when the downstream customer uses a dereserved input and 0 otherwise. *UpDereserv* is a dummy that equals 1 when the reserved product market that uses intermediate inputs from the upstream is dereserved and 0 otherwise. Errors are robust clustered at the product- level and weighted by the initial labor shares. Standard error in parentheses.$^{*}p < 0.10$, $^{**}p < 0.05$,$^{***}p < 0.01$