

Cost Shocks and Production Reorganization: Evidence from India's Goods and Services Tax Reform

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Manufacturing firms routinely face exogenous cost shocks—such as taxes, tariffs, and regulatory shifts—that alter their cost structures, forcing a fundamental trade-off between reorganizing production to minimize direct costs and maintaining established production “recipes” to preserve efficiency. This paper examines this dilemma using India’s 2017 Goods and Services Tax (GST) reform as a natural experiment which introduced heterogeneous effective tax changes across plants by unifying taxes and eliminating cascading input taxes. Leveraging granular plant-level data from 72,000 manufacturing facilities over nine years, we employ a continuous difference-in-differences (DiD) design to track plant responses. We find that plants facing larger tax increases systematically shift product portfolios toward lower-rate categories. We distinguish between reclassification (minor product modifications that preserve existing production capabilities) and reorganization (fundamental operational restructuring with new inputs). Resource-constrained plants favor low-cost reclassification, while larger, capital-intensive plants pursue reorganization. These adjustments, however, come at a steep operational cost: total factor productivity (TFP) declines by 2.2 percent for every 10 percentage-point increase in effective tax rates. This decline is driven by a “quantity-for-quality” substitution in material sourcing, where plants switch to lower-quality domestic inputs to cut costs, eroding material efficiency despite simultaneous gains in labor, capital, and inventory productivity. Taken together, these patterns reveal a clear cost-efficiency trade-off: plants lower their effective tax and working-capital burdens through portfolio shifts, input substitution, and leaner inventories, but accept lower production efficiency in return. Our findings provide actionable insights for managers building operational resilience and for policymakers on mitigating unintended productivity losses from heterogeneous policy shocks.

Key words: empirical operations management, manufacturing operations, production organization, total factor productivity, input sourcing, tax reform, natural experiment

1. Introduction

Manufacturing firms routinely face large, exogenous shocks that fundamentally alter their cost structures. These shocks can stem from various sources, including shifting trade policies, environmental regulations, tariff adjustments, supply chain disruptions, technology mandates, or tax reforms. While existing literature has documented the impact of such macro shocks on aggregate firm outcomes, including investment and hiring responses (Bloom 2009), plant-level adjustment dynamics (Caballero et al. 1995), and network-level propagation (Carvalho 2014, Barrot and Sauvagnat 2016), much less is known about the within-plant operational mechanisms firms use to adapt in response to these shocks. This paper investigates a first-order question: *how do manufacturing operations adapt to sudden, large-scale shocks?* Specifically, we examine how plants reorganize their product portfolios, reconfigure input sourcing, adjust production processes, and manage inventories under intense cost pressure. Understanding these operational responses extends beyond any single policy context to

contemporary challenges including carbon pricing, shifting tariffs, and geopolitical fragmentation that similarly force firms to reorganize production under cost pressure.

When such shocks occur, firms face a fundamental cost-efficiency trade-off: should they aggressively reorganize production to minimize new costs, or maintain existing operations to preserve efficiency? This dilemma is central to operations management. On one hand, adapting—by changing product portfolios, sourcing strategies, or inventory policies—can minimize the direct cost burden of the shock. On the other hand, such adaptation is not free; it risks disrupting established production “recipes” that have been optimized for efficiency over time. This paper examines this dilemma, asking whether firms should prioritize minimizing new costs or maintaining operational continuity to preserve productivity.

The limited empirical evidence on how firms navigate this trade-off stems from a critical data challenge: examining internal reorganization requires highly granular *product-by-plant input-output data*, which is rarely available at scale. While prior studies of multi-product firms have examined product scope adjustments in response to trade shocks (Bernard et al. 2010, 2011) and have documented supply chain responses to tariffs and natural disasters (Handley et al. 2024, Carvalho 2014, Boehm et al. 2019), these studies typically only observe aggregate revenue and trade flows rather than the detailed internal production decisions—such as the specific input “recipes” and resource allocations used on the factory floor. This limitation persists because plant-level production micro-data is generally confidential and restricted-access, hindering efforts to open the “black box” of operational decision-making within manufacturing plants.

We address this challenge by leveraging unusually granular plant-level production micro-data from India, combined with a large-scale natural experiment: the 2017 Goods and Services Tax (GST) reform. Our analysis exploits data from the Annual Survey of Industries (ASI), covering approximately 72,000 manufacturing plants over nine years (2014/15–2022/23). This dataset provides exceptional granularity, reporting each plant’s inputs and outputs at the individual product level—including quantities, values, and tax classifications for every input item consumed and every output product manufactured. Beyond itemized production, we observe comprehensive plant-level operational metrics, including employment, wage bills, net fixed assets (capital), and energy consumption (electricity and fuel). This multi-dimensional data allows us to open the black box of factory-floor decisions, enabling us to track not only how plants reorganize their “product recipes” but also how they reallocate labor and capital in response to the massive fiscal transition induced by the GST reform.

The implementation of the Goods and Services Tax (GST) represented a landmark tax reform in India’s fiscal history. It replaced a fragmented system of state- and center-level taxes with a unified national value-added tax, eliminating the pre-GST regime’s “tax cascading”, where input

taxes were not fully creditable against the output tax. This tax-on-tax distortion amplified the effective tax burdens at every production stage, penalizing multi-stage manufacturing. However, this unification was not uniform, as the new system introduced multiple tax slabs ranging from 5% to 28%, creating heterogeneous cost shocks across plants due to their unique input-output mixes.¹ This exogenous variation enables us to identify how plants reconfigured their production processes and product portfolios under cost pressures, while measuring the subsequent impact on operational performance.

Our identification strategy employs a continuous difference-in-differences design based on a time-invariant plant-specific measure of *effective tax change from the GST reform*, which incorporates both the output tax rate changes and the elimination of input tax cascading. We compare how operational outcomes evolve across plants facing varying effective tax changes—ranging from substantial increases to significant reductions. Rather than imposing arbitrary treatment thresholds, our continuous treatment approach exploits the full spectrum of tax exposure across plants. Our specification includes plant and year fixed effects as well as time-varying controls, and we formally validate the identification strategy by confirming that plants followed parallel trends prior to the reform.

Our analysis proceeds in four steps. First, we examine how plants reshape their output product portfolios across different GST tax brackets² to mitigate effective tax exposure. Second, we unpack these portfolio changes and ask how plants implement them in practice, distinguishing between low-cost reclassification (minor product modifications) and deeper reorganization (fundamental operational restructuring), while exploring how resource availability influences these choices. Third, we evaluate the operational efficiency implications of these adjustments by estimating plants' total factor productivity (TFP) and quantifying the overall impact on TFP. Fourth, we examine inventory and working-capital management as a complementary operational dimension, assessing whether plants tighten inventory policies amid rising tax-inclusive costs.

We begin by analyzing how plants reshape their output portfolios post-reform. Using product-year-level data on sales and GST classifications, we construct measures of each plant's sales-weighted average GST rate³ and track how the number and sales share of products in each tax bracket evolve in response to reform exposure. This approach reveals whether plants leverage their product mix to alleviate tax burdens. We find that plants facing larger tax increases systematically rebalance their

¹On the output side, differential GST rates (0% to 28%) across product categories generated a tax wedge between producer and consumer prices, eroding profitability of high-rate products and incentivizing shifts toward lower-tax categories. On the input side, comprehensive Input Tax Credits (ITC) eliminated the prior cascading “tax-on-tax” problem

²The GST system has five main tax brackets: 0%, 5%, 12%, 18%, and 28%, with different products assigned to different brackets.

³For each plant-year, we weight each product's GST rate by its share of the plant's total sales, yielding a portfolio-level average tax rate.

product portfolios toward lower-rate brackets, reducing the share of high-rate products and hence, effectively lowering the sales-weighted GST rate. Specifically, a 10 percentage-point increase in effective tax burden reduces a plant portfolio's average GST rate by 0.38 percentage points relative to less-exposed plants. These adjustments are persistent, unfold gradually over post-reform years, and scale with each plant's tax increase, indicating active product-mix reconfiguration to mitigate the impact of indirect tax hikes.

Given these pronounced output adjustments, we next investigate *how* plants implement these changes in practice and what adjustment costs they incur. To answer this, we develop a novel measure of product similarity based on input composition, using the cosine similarity of input cost-share vectors to quantify the resemblance between product “recipes.” This allows us to distinguish between two operational strategies: *reclassification*, where new products closely mirror existing input structures, requiring only minor modifications or relabeling to access favorable tax categories⁴ and *reorganization*, where new products entail substantially different input requirements, reflecting deeper changes in technology, suppliers, or production processes. We find that plants facing larger effective tax increases disproportionately rely on reclassification, introducing products that are highly similar to their existing ones. Conversely, plants experiencing smaller tax increases or reductions lean toward reorganization, adding products with distinct input structures. This suggests that acute cost shocks prompt plants to prioritize low-cost, incremental adjustments that preserve operational capabilities.

The strategic choice between reclassification and reorganization, however, hinges on plant resources. We find that larger plants facing the same tax shocks are significantly *less* inclined toward reclassification and more prone to genuine reorganization. This pattern reveals a resource-based perspective on adjustment strategies: capital-constrained plants opt for low-fixed-cost reclassification despite its limitations, while resource-abundant ones invest in deeper reorganization that may deliver superior long-term performance. These findings underscore that operational responses to cost shocks are shaped not only by the shock magnitude but also by the internal capabilities and resources firms can deploy. We formalize this trade-off in a simple theoretical model that maps these adjustment decisions to firm scale and the magnitude of the shock.

These portfolio adjustments have substantial consequences for operational efficiency. We quantify efficiency using total factor productivity (TFP), estimated via a revenue-based Cobb-Douglas production function with capital, labor, and materials as inputs. We find that plants exposed to larger effective tax increases suffer significant *declines* in TFP: a 10 percentage-point increase in

⁴This is especially feasible under GST due to the rate disparities among closely related products. For example, milk is taxed at 5% while ice cream faces 18%, and bread at 0-5% while biscuits face 18%. This creates opportunities to lower tax exposure through minor product modifications.

the effective tax rate is associated with a 2.2% drop in overall productivity. This efficiency loss is puzzling at first glance. A closer examination reveals that this decline masks a striking divergence in partial productivity measures. Specifically, while affected plants actually improve their labor and capital productivity, thereby producing more output per worker and unit of capital, these gains are more than offset by a sharp deterioration in material productivity. We uncover that the root cause lies in input sourcing decisions. To mitigate costs, plants facing higher tax burdens substitute imported inputs with domestic alternatives. However, this switch comes at a quality cost: plants consume significantly larger quantities of domestic materials per unit of output, suggesting that domestic inputs are of lower yield or specification. This “quantity-for-quality” substitution erodes material efficiency, ultimately driving down aggregate plant productivity.

Beyond production efficiency, we examine a complementary dimension of operational performance: inventory productivity, which captures the efficiency of working capital management. We hypothesize that higher effective tax rates increase the tax-inclusive inventory holding cost, raising the opportunity cost of working capital and thus creating strong incentives to tighten working capital cycles. Consistent with this mechanism, we find that plants facing larger effective tax increases significantly improve their inventory turnover, particularly for work-in-process (WIP) and finished goods. Specifically, adjusted turnover rates rise and days-of-inventory decline, indicating that affected plants successfully accelerate the conversion of inventory into sales to free up cash tied in working capital.⁵ These findings suggest that cost shocks induce a “leaner” operational discipline, forcing plants to minimize tied up capital despite the concurrent drag on TFP.

Taken together, these findings reveal a fundamental cost–efficiency trade-off in manufacturing plants responding to exogenous cost shocks. Plants mitigate the direct burden of the shock through three complementary mechanisms: reshaping product portfolios toward lower-tax categories, substituting toward cheaper domestic inputs, and streamlining inventory to free up cash tied in working-capital. However, these cost-minimizing adjustments come at the expense of production efficiency. While these adjustments boost labor, capital, and inventory productivity, they severely erode material productivity due to the substitution of lower-quality domestic inputs, ultimately driving a net decline in total factor productivity (TFP). We further show through our theoretical model that the severity of this trade-off is mediated by the magnitude of the shock and the plant’s resource endowment. These dynamics extend beyond tax reforms to diverse contemporary challenges, including carbon pricing, shifting tariffs, and geopolitical fragmentation, underscoring a pervasive tension between cost minimization and operational stability in modern manufacturing.

⁵Raw-material inventories show smaller improvements, consistent with the greater contractual rigidities and lead-time frictions that constrain upstream adjustments.

Our paper makes several contributions to the operations management literature. First, we identify the granular operational levers firms deploy to manage exogenous cost shocks. While prior literature typically treats adaptation as an aggregate adjustment of capital or labor Bloom (2009), we exploit item-level production data to show that firms actively re-engineer their production recipes to navigate cost pressures. In doing so, we provide one of the first empirical examinations in operations management of how manufacturing plants reorganize their physical production processes in response to large-scale regulatory shocks. Second, we expand the understanding of product portfolio management. Traditional OM theory views product assortment as a response to consumer demand or capacity constraints; we demonstrate that regulatory cost structures can act as a primary driver of portfolio design, incentivizing firms to alter product architectures specifically to leverage tax arbitrage. Third, we uncover the operational consequences of financial hedging. We document a “quantity-for-quality” substitution in sourcing, showing that while supply chain shifts can mitigate direct financial costs, they introduce friction into the production process—manifesting as lower material quality and reduced total factor productivity. This highlights a critical, often overlooked cost of flexibility: financial optimization strategies can structurally erode process efficiency.

The remainder of this paper proceeds as follows. §2 reviews the related literature. §3 describes the institutional background of India’s GST reform. §4 presents the data and measurement strategy. §5 outlines the empirical methodology. §6 presents the main results on output portfolio adjustments. §7 examines the distinction between reclassification and reorganization. §8 analyzes the efficiency consequences, focusing on total factor productivity and input sourcing. §9 investigates inventory productivity and working-capital management. §10 discusses the broader managerial implications and concludes.

2. Related Literature

Our paper contributes to three related streams of literature in operations management and economics: (i) product portfolio adjustment by firms, (ii) the role of tax policy in shaping firms’ operational decisions, and (iii) the determinants of operational productivity and efficiency. Below, we summarize the relevant papers from these literature streams and highlight our contribution relative to them.

2.1. Product Portfolio Adjustment:

Our paper contributes to the literature on firms’ product portfolio decisions. Prior work in operations management has investigated internal drivers of product scope, including production flexibility (Bansal and Nagarajan 2017, Goyal and Netessine 2011, Boyabatlı et al. 2016), dynamic pricing (Ceryan et al. 2013, Moreno and Terwiesch 2015), and customer preferences (Yunes et al. 2007, Mendelson and Parlaktürk 2008). A smaller, but relevant stream of literature studies external shocks such as tariffs and environmental regulations and their impact on product scope. For instance,

Muthulingam et al. (2022) study how environmental regulations influence operational decisions. Similarly, Dong and Kouvelis (2020) show analytically how firms reallocate resources across products and markets in response to tariff-induced cost increases. Despite these studies, empirical evidence on how domestic indirect taxes shape firms' product portfolios is quite limited.

We address this gap using product-level data from India's Annual Survey of Industries (ASI), a rich plant-level dataset widely used in economic research (Boehm and Oberfield 2020, Allcott et al. 2016, Orr 2022). Using this data, we track how plants reorganize their product mix across different tax slabs in response to tax-induced cost changes.

2.2. Tax Policy and Plant's Operational Decisions:

Our paper also extends research on how tax policy influences firms' operational choices. Prior operations management studies have focused mainly on international tax planning, including the strategic use of tax incentives in global supply chains (Hsu and Zhu 2011), capacity decisions under cross-crediting (Xiao et al. 2015), transfer pricing (Shunko et al. 2014), and the effects of tariffs on network design (Dong and Kouvelis 2020).

Another related strand examines carbon taxes and their impact on technology choice, emissions, and profitability (Drake 2018, Fan et al. 2023). While insightful, this work is largely analytical and centers on cross-border contexts. As such, empirical evidence on domestic taxes remains scarce.

Finally, some recent economic studies have studied VAT reforms empirically and document effects on outcomes such as sales, input procurement, wages, and capital (Agrawal and Zimmermann 2025, Hoseini and Briand 2020). These papers provide a convincing economic analysis of VAT but offer limited detail on within-firm operational margins. To our knowledge, we provide one of the first empirical analyses of how *domestic indirect taxes* affect firms' operational decisions, including product portfolio management, production efficiency, input sourcing and inventory management, rather than focusing solely on prices or aggregate performance.

2.3. Productivity and Operational Efficiency:

Finally, we study how tax-induced cost shocks affect productivity and operational efficiency. For manufacturers, productivity is typically defined as the efficiency with which multiple inputs are transformed into output (Syverson 2011). Prior research links productivity to supply network formation (Arora and Osadchiy 2025) and financial performance (Jacobs et al. 2016, Modi and Mishra 2011), and examines how supply chain structure (Serpa and Krishnan 2018), workforce characteristics (Moon et al. 2023), leadership (Giardili et al. 2023), and new product introduction (Gopal et al. 2013) shape productivity. Methodologically, most of this work relies on total factor productivity (TFP) measures constructed from production data under cost-minimization assumptions or estimated production functions (Syverson 2011).

Operations management research also emphasizes narrower operational metrics such as inventory productivity. Gaur et al. (2005) introduce the adjusted inventory turnover measure, which has been applied in several subsequent studies (Alan et al. 2014). Building on these literatures, we use GST-induced variation in firms' tax burdens to examine how domestic indirect tax shocks affect both broad productivity measures and inventory productivity, showing that such tax-induced cost changes not only reshape firms' product scope and input sourcing but also alter the efficiency with which they use inputs and working capital.

3. India's 2017 Goods and Services Tax Reform

On July 1, 2017, India implemented the Goods and Services Tax (GST) system, a nationwide reform of indirect taxation.⁶ The GST replaced a fragmented system of central, state, and local levies with a unified, destination-based value-added tax on goods and services. Its goals included harmonizing tax rates across states and products, removing cascading taxes along supply chains, and strengthening compliance via digital reporting.

3.1. Pre-Reform Indirect Tax System

Prior to GST, India's indirect tax regime featured multiple levies, including Central Excise Duty (CENVAT) at the manufacturing stage, State value-added tax (VAT) on intra-state sales, and Central Sales Tax (CST) plus entry taxes on inter-state shipments. Administered by separate authorities, these imposed distinct registration, filing, and audit requirements, especially for firms having multi-state operations.⁷ As a result, goods could be taxed multiple times at different stages of production and distribution. In many cases, firms could not offset the tax paid under one levy against liability under another. For example, CST collected by the origin state could not be credited elsewhere.

This structure generated two key distortions. First, tax rates varied by state and product, raising compliance costs. Second, limited input tax credits led to "tax on tax" cascading, where taxes accumulated on values already embedding prior levies—a distortion exacerbated in multi-stage or inter-state supply chains (See Online Appendix Figure OA.1 for an illustration). This makes the pre-GST system different from a pure VAT system where firms only pay taxes on the value added in the supply chain.

⁶Indirect taxes are levied on transactions in goods and services, with the tax remitted by firms but typically passed on to consumers through tax-inclusive prices.

⁷For a detailed overview of the pre-GST taxes, see Online Appendix Table OA.1.

3.2. GST Reform Design and Implementation

The GST consolidated this fragmented structure into a single nationwide system co-administered by the central and the state governments. A core design element of GST is the input tax credit (ITC): registered firms collect GST on the value of their sales and remit it net of credits for taxes paid on purchases, including inter-state taxes. In this way, firms only pay tax on the value they add in the supply chain. This largely removed the cascading problem of the old regime, streamlined administration and facilitated better inter-state trade.

The GST rate schedule consists of four main slabs, 5, 12, 18, and 28 percent, plus exemptions for basic necessities. Table 1 lists illustrative product categories for each slab. Combined with the ITC, these slabs determine the net tax burden on each product in our analysis.

GST Rate	Description
Exempted	Unprocessed food items, fresh produce, other basic necessities
5%	Coal, essential food items, life-saving drugs, low-value textiles and apparel
12%	Processed foods, medical equipment, wood products, mid-range textiles and apparel
18%	Packaged foods and beverages, cosmetics, machinery, industrial goods
28%	Automobiles, air conditioners, private aircraft, other luxury items

Table 1 GST Rates and Illustrative Product Categories

3.3. Heterogeneous Cost Shocks from GST

The GST reform created cost shocks for manufacturing plants through two channels. On the output side, the reform created a tax wedge between producer and consumer prices.⁸ This tax wedge alters the demand conditions facing the firm: plants producing goods that moved into higher GST brackets faced higher tax-inclusive prices for a given producer price, reducing their competitiveness relative to lower-taxed alternatives. Whether this wedge manifests as reduced demand (via pass-through) or compressed margins (via absorption), it creates strong incentives for plants to rebalance product portfolios toward lower-rate categories. On the input side, the ITC mechanism reduced the cascading tax burden on the inputs. These two channels combined to create substantial heterogeneity in effective tax exposure across plants. A plant's net effective tax shock thus depends on how the GST rates on its outputs changed relative to pre-GST rates and how much of its input tax burden was previously non-creditable under the cascading system. We describe the construction of plant-specific effective tax change in §4.2.

⁸With products classified into five main tax slabs (0%, 5%, 12%, 18%, and 28%), the final consumer price becomes $P_{\text{buyer}} = (1 + \tau^{\text{GST}})P_{\text{producer}}$.

4. Data and Descriptive Evidence

We construct our sample from multiple data sources: (i) three tax-rate databases and (ii) a plant-level dataset from the Annual Survey of Industries (ASI). In this section, we describe these data sources, present model-free evidence on tax exposure and product portfolio shifts, define our main treatment variable, and provide summary statistics for our estimating sample.

4.1. Tax Databases and Plant-Level Production Data

To measure tax changes by the reform, we assemble three product-level tax datasets. First, we obtain pre-GST central excise duties at the 6-digit HS level from the Indian Finance Ministry's Department of Revenue.⁹ Second, we use the panel VAT dataset compiled by Agrawal and Zimmermann (2025), which reports detailed pre-GST state-product-time VAT rates. Third, we collect the post-GST rate schedule from the GST Council, assigning each HS code to a slab (0, 5, 12, 18, or 28 percent, with special rates for a small set of products).¹⁰ Figure 1 shows pre-GST VAT rates across industries and states, revealing substantial variation: some states, such as Delhi, used relatively uniform VAT schedules, while others applied varied rates across multiple industries. Post the reform, a national schedule reduced cross-state differences, creating heterogeneous tax shocks that we exploit empirically.

Second, we use plant-level ASI data for fiscal years 2014/15 to 2022/23. The ASI is India's main survey of registered manufacturing plants. It samples all large plants above a size threshold (varying by state from 50 to 100 employees) and a rotating subset of smaller plants. Large plants are surveyed annually, while smaller plants are surveyed once every three to five years.¹¹

The ASI is well suited to study the GST reform for three reasons. First, it provides a long panel of plants that we can follow before and after the reform. Second, it collects very granular information on plant operations, including capital, employment, materials, energy, inventories, and financial flows. Third, a distinctive feature of the ASI is its high-quality, product-level data on *both inputs and outputs*. Specifically, it records product-level quantities and values for both inputs and outputs using the National Product Classification for Manufacturing Sector (NPCMS), which we harmonize with HS codes to merge in tax rates.

The dataset's scope allows us to construct all key variables. From the asset and liability side (Blocks C, D, F), we obtain fixed assets, loans, and working capital items (raw materials, work-in-process, and finished goods). From the flow side (Blocks E, H, I, J), we derive employment, wages,

⁹<https://www.cbic.gov.in/entities/cbic-content-mst/MTYz>

¹⁰<https://gstcouncil.gov.in/cgst-rate-notification?page=0>

¹¹ASI assigns each plant a sample weight based on the ratio of the total number of plants in a stratum to the number actually surveyed in that stratum. We use these weights in our analyses for representative estimates. We provide details of the sampling design in Online Appendix OA.2.

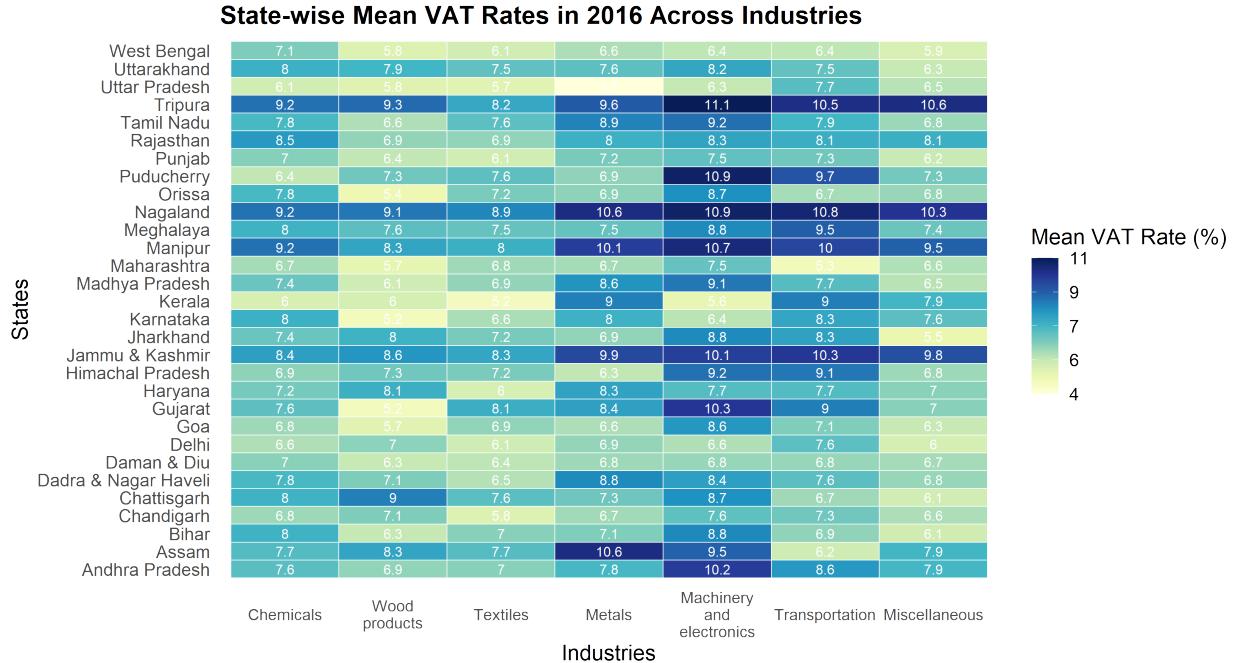


Figure 1 State-wise Mean VAT Rates in 2016 Across Industries

the value of indigenous and imported inputs consumed, and detailed product-level information on quantities manufactured and sold. We provide a complete list of the ASI blocks and variables used in Online Appendix Table OA.2.

4.2. Treatment Variable and Summary Statistics

Our main treatment variable is a plant-level effective tax change rate, τ_i^E , where i indexes plants. The variable combines two main features of the GST reform discussed in Section 3: the change in the tax rate on a plant's output basket and the removal of cascading input taxes through the input tax credit (ITC) mechanism. Following Agrawal and Zimmermann (2025), we define

$$\tau_i^E = \underbrace{\tau_i^O}_{\text{Output tax change}} + m_i \left(\underbrace{0}_{\text{post-GST cascading burden}} - \underbrace{\alpha \tau_i^{I,\text{Pre}}}_{\text{pre-GST cascading burden}} \right), \quad (1)$$

where τ_i^O is the plant's output tax rate change, $\tau_i^{I,\text{Pre}}$ is its pre-GST input tax rate, m_i is the share of material costs in total operating costs, and $\alpha \in [0, 1]$ is the pre-GST cascading factor that captures the share of input taxes that were effectively non-creditable. Thus, the term in parentheses measures the change in the non-creditable input tax burden between the pre-GST regime and the GST regime. Under GST, we assume that cascading is eliminated, so the post-GST burden is zero.

The first component in Equation (1), τ_i^O , captures changes in the tax rate on the plant's output basket:

$$\begin{aligned}\tau_i^O &= \tau_i^{O,\text{Post}} - \tau_i^{O,\text{Pre}}, \\ \tau_i^{O,\text{Post}} &= \sum_p s_{ip} \tau_p^{\text{Post}}, \quad \tau_i^{O,\text{Pre}} = \sum_p s_{ip} \tau_p^{\text{Pre}},\end{aligned}\tag{2}$$

where p indexes products, τ_p^{Post} and τ_p^{Pre} are the post-GST and pre-GST (central excise plus VAT) rates at the HS level, and s_{ip} is product p 's share in plant i 's total pre-GST gross sales, aggregated over 2014/15–2016/17. Thus τ_i^O is the change in the plant's sales-weighted output tax rate induced by the reform.¹²

The second component in Equation (1), $\tau_i^{I,\text{Pre}}$, is the pre-GST tax rate on plant i 's input bundle:

$$\tau_i^{I,\text{Pre}} = \sum_k w_{ik} \tau_k^{\text{Pre}},\tag{3}$$

where k indexes input items, τ_k^{Pre} is the pre-GST tax rate (excise plus VAT) on input k , and w_{ik} is the share of input k in plant i 's total material purchases over 2014/15–2016/17, so that $\sum_k w_{ik} = 1$. This object is the expenditure-weighted average pre-GST tax rate on the plant's material inputs.

Finally, the cascading factor α links the above input tax measure to the ITC discussion in Section 3. Under the pre-GST regime, only a fraction of input taxes could be credited, so a share α of $\tau_i^{I,\text{Pre}}$ cascaded into production costs. Previous work places α in the range 0.35 to 0.40 (Ahmad and Poddar 2009). In our baseline specification we set α to 0.35 and show that our results are robust to alternative values of α around it. The term $m_i \alpha \tau_i^{I,\text{Pre}}$ therefore captures the contribution of non-creditable input taxes to pre-GST production costs, scaled by the importance of materials in the plant's cost structure. A higher τ_i^E reflects either a larger increase in the plant's output tax rate or a smaller reduction in cascading input taxes that the plant enjoys under GST. Online Appendix Table OA.3 provides a worked example of our construction of the treatment variable.

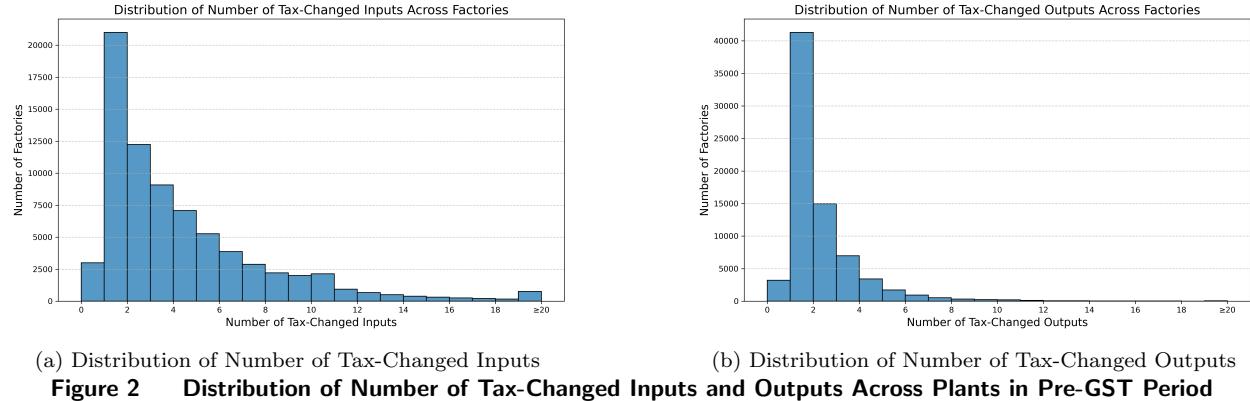
Summary Statistics: Our final sample includes 72,340 plants with production activity from 2014/15 to 2022/23. Table 2 reports key summary statistics. The effective tax change rate τ_i^E averages -6.2 percentage points with a standard deviation of 7.0 percentage points, indicating average tax relief with substantial variation across plants: some experience tax cuts, while others face sizable tax increases. Our empirical design exploits this cross-sectional variation in τ_i^E , and throughout the paper “higher” or “larger” tax changes refer to plants in the right tail of this distribution that face tax increases.

¹²Importantly, we hold the pre-GST sales mix fixed when constructing τ_i^O ; the treatment variable does not incorporate any post-reform adjustments in the output portfolio.

The sales composition by GST rate shows that products taxed at 12–18% account for the largest share of sales. Products in the lower tax brackets (below 12%) also make up a substantial portion, while those taxed above 18% represent a relatively small share. Firms' output portfolios are highly concentrated, and the value is consistent with sales breakdown. Over half of the plants produce only one product, with the median equal to one product. On the input side, the purchase value of materials is the largest cost component, with a log value of 17.885. In inventory holdings, work-in-progress (WIP) shows the highest turnover rate, while raw materials turn over more slowly, indicating variation in inventory efficiency across stages of production.

4.3. Model Free Evidence

Before turning to econometric analysis, we present descriptive evidence on the prevalence of tax-affected products and portfolio reallocation following GST. Figure 2 shows that the vast majority of plants experienced GST-induced tax changes in at least one input and one output, indicating widespread exposure to the reform. Online Appendix Figure OA.3 further demonstrates substantial reallocation of output portfolios across GST tax brackets, with many plants significantly increasing or decreasing their sales shares in specific brackets after the reform, rather than maintaining their pre-reform product mix.



5. Empirical Methodology

In this section, we describe our empirical strategy. We examine a panel of plants $i \in \{1, \dots, I\}$ observed over years $t \in \{1, \dots, T\}$. Let y_{it} denote plant i 's outcome variable in year t . We use a continuous difference-in-differences (DiD) design in which treatment intensity is given by a time-invariant plant-level exposure, the effective tax change τ_i^E . Our baseline specification is:

$$y_{it} = \beta_0 + \beta_1 \tau_i^E \times Post_t + \phi' X_{it} + \lambda_i + \gamma_t + \epsilon_{it}. \quad (4)$$

Table 2 Summary Statistics

	N	Mean	Std	25 Percentile	Median	75 Percentile
<i>Panel A. Treatment Variable and Its Components</i>						
Effective tax change rate	72,340	-0.062	0.070	-0.103	-0.050	-0.022
Output tax change rate	72,340	-0.029	0.064	-0.065	-0.017	0.005
Share of material cost	72,340	0.669	0.247	0.537	0.738	0.859
Pre-GST input tax rate \times cascading factor	72,340	0.049	0.024	0.026	0.058	0.063
<i>Panel B. Dependent Variables</i>						
Total number of outputs	298,353	1.777	1.497	1.000	1.000	2.000
Number of outputs with GST $\leq 5\%$	298,353	0.405	0.881	0.000	0.000	0.000
Number of outputs with GST in (5%, 12%]	298,353	0.390	0.890	0.000	0.000	1.000
Number of outputs with GST in (12%, 18%]	298,353	0.858	1.094	0.000	1.000	1.000
Number of outputs with GST $> 18\%$	298,353	0.124	0.408	0.000	0.000	0.000
Sales-weighted average GST rate of output portfolio	298,339	0.132	0.063	0.085	0.150	0.180
Number of reclassified new outputs (0.7)	298,353	0.102	0.374	0.000	0.000	0.000
Number of reclassified new outputs (0.8)	298,353	0.078	0.317	0.000	0.000	0.000
Number of reclassified new outputs (0.9)	298,353	0.045	0.233	0.000	0.000	0.000
Number of reorganized new outputs (0.7)	298,353	0.250	0.729	0.000	0.000	0.000
Number of reorganized new outputs (0.8)	298,353	0.274	0.773	0.000	0.000	0.000
Number of reorganized new outputs (0.9)	298,353	0.308	0.825	0.000	0.000	0.000
Total factor productivity (ln)	294,933	3.065	1.534	2.186	2.669	3.651
Gross sales/total cost of materials (ln)	295,971	0.421	0.403	0.190	0.361	0.599
Gross sales/total cost of labor (ln)	296,648	2.531	1.091	1.843	2.484	3.171
Gross sales/total number of employees (ln)	296,648	14.147	1.314	13.391	14.192	14.990
Gross sales/total capital stock (ln)	296,647	1.714	1.691	0.866	1.642	2.446
Total cost of materials (ln₹)	295,971	18.095	2.342	16.316	18.285	19.807
Cost of domestic items (ln₹)	300,023	17.560	2.901	15.959	17.946	19.456
Cost of imported items (ln₹)	300,023	3.795	7.334	0.000	0.000	0.000
Cost of energy input (ln₹)	296,234	15.109	2.303	13.530	15.089	16.696
Adjusted inventory turnover for raw materials (ln)	207,425	0.646	1.062	-0.071	0.496	1.169
Adjusted days of inventory for raw materials (ln)	207,425	5.254	1.062	4.731	5.404	5.971
Adjusted inventory turnover for WIP (ln)	113,615	1.853	1.352	0.877	1.716	2.670
Adjusted days of inventory for WIP (ln)	113,615	4.046	1.352	3.230	4.184	5.023
Adjusted inventory turnover for finished goods (ln)	179,960	1.272	1.196	0.438	1.149	1.969
Adjusted days of inventory for finished goods (ln)	179,960	4.628	1.196	3.930	4.751	5.462
<i>Panel C. Control and Moderating Variables</i>						
Total number of workers (ln)	303,067	4.352	1.609	2.944	4.511	5.545
Gross asset (ln₹)	303,068	16.854	2.608	15.066	16.956	18.662
Export share	303,068	6.038	21.128	0.000	0.000	0.000
Number of new outputs	298,353	0.352	0.882	0.000	0.000	0.000
Pre-GST average capital size (ln)	318,271	16.628	2.610	14.842	16.731	18.437

where the variable $Post_t$ equals 1 for fiscal years 2017/18 and onward, marking the onset of the GST reform.¹³ X_{it} is a vector of controls that includes the log total number of workers and log total assets to account for plant size. Additionally, we include the export share of gross sales to account for policy incentives that may influence output decisions, as detailed in Online Appendix OA.1. In addition, we include plant fixed effects λ_i and year fixed effects γ_t . Our main coefficient of interest

¹³The Indian fiscal year starts from April 1 to March 31 of the following year, which aligns with the ASI data collection cycle. The GST reform came into effect on July 1, 2017.

is β_1 , which measures post-reform outcome changes per unit increase in exposure τ_i^E . Intuitively, the design compares plants with different exposure intensities τ_i^E before and after the GST reform.

We also estimate an event study version of Equation (4), which is given by:

$$y_{it} = \beta_0 + \sum_{k=-3}^{5} \beta_k \mathbb{1}\{t = \mathcal{T} + k\} \times \tau_i^E + \phi' X_{it} + \lambda_i + \gamma_t + \epsilon_{it}, \quad (5)$$

where $\mathbb{1}\{t = \mathcal{T} + k\}$ are event time dummies, $\mathbb{1}\{\cdot\}$ is an indicator function and \mathcal{T} is the year when GST is first implemented. We follow the standard practice in literature to use the “period before the treatment” as a normalizer (Miller 2023) and set β_{-1} equal to zero. Our key identifying assumptions are:

Assumption 1 (Parallel trends in untreated outcomes). *Absent GST, plants with different τ_i^E would follow the same trend in outcomes, conditional on plant and time fixed effects and controls.*

Assumption 2 (No anticipation). *Plants do not anticipate treatment. Specifically, the tax rate changes cannot predict outcome changes prior to the GST reform.*

Assumption 3 (Common support). *The distributions of the covariates (X_i) overlap across different treatment groups.*

Assumption 4 (Exogenous treatment). *The treatment is exogenous, and lagged changes in outcome variables pre-GST reform do not predict subsequent changes in treatment intensity.*

To validate parallel trends, we estimate the event study coefficients in Equation (5). Figure 3 plots these coefficients and shows that plants with different τ_i^E followed the same trends in outcomes before the GST reform, consistent with our parallel trends assumption. To test for anticipation, we estimate pre-reform regressions of changes in the outcome variables on τ_i^E , using the same controls and fixed effects as in Equation (4) but restricting the sample to fiscal years before 2017/18. Appendix Table OA.4 reports that the coefficients on τ_i^E in these pre-GST regressions are small and statistically insignificant, indicating no anticipatory adjustments.

To test the assumption of common support, we examine the median and the ranges between the 5th and 95th percentiles of two key covariates (total assets and number of employees) across four groups of plants, each categorized by the percentile of the effective tax change rate. The large overlapping ranges across four groups support this assumption as shown in Appendix Figure OA.4. Finally, to test for treatment exogeneity, we examine whether lagged changes in outcome variables influence subsequent changes in treatment intensity. Since the GST reform happened in 2017 and the treatment intensity changed in 2017/18, we choose this year as our sample period. We estimate Equation (OA.2), where β_1 denotes the effect of lagged outcome changes on the effective tax change rate. Appendix Table OA.5 shows that the coefficients are all insignificant, confirming exogenous treatment.

6. Impact on Plants' Output Product Portfolio

In this section, we examine how the GST reform reshaped plants' output product portfolios across different tax brackets. When tax rates differ sharply across products, plants can lower their effective tax burden not only by adjusting volumes within products (an intensive-margin response) but also by changing the set of products they offer across different GST tax slabs (an extensive-margin response). To capture these portfolio-level adjustments, we categorize each plant's outputs into four GST rate groups: (i) 5% or below, (ii) (5%, 12%], (iii) (12%, 18%], and (iv) greater than 18%.¹⁴ For plant i in year t and GST bracket g , we define the number of unique output products in tax bracket g as:

$$N_{igt} \equiv \sum_{p:r_p \in g} \mathbb{1}\{y_{ipt} > 0\}, \quad (6)$$

where y_{ipt} denotes plant i 's quantity of product p in year t and r_p is the GST rate applicable to product p . This exercise allows us to ask whether plants use their product mix as a lever to reduce their tax burden.

6.1. Output Portfolio Adjustment Post-GST Reform

We first estimate GST's impact on plants' output product portfolio using Equation 4. Table 3 shows the results. Column (1) shows that plants with higher effective tax change rates increase their total number of outputs. The corresponding regression coefficient is 0.151, which implies that a 0.10 (10 percentage-point) higher effective tax change rate (τ^E) between two plants is associated with 0.015 more output products after the GST reform, on average.

Second, we document heterogeneous portfolio responses across different GST tax brackets. We find that plants exposed to larger tax increases (higher τ_i^E) significantly expand the number of distinct products they offer in the lowest tax slab ($\leq 5\%$) while reducing the number of products in the highest slab ($> 18\%$), as shown in Columns (2)-(5).¹⁵ By contrast, the coefficients for the number of outputs in the intermediate brackets (5%, 12%] and (12%, 18%] are small and statistically insignificant. These portfolio adjustments indicate that plants facing higher effective tax burdens strategically rebalance their output portfolio toward low tax items and away from highly taxed ones. Similar patterns hold for gross sales (Appendix OA.5), indicating strategic rebalancing toward lower-tax items.

¹⁴As shown in Table 1, products under GST are taxed at 0, 5%, 12%, 18%, or 28%. Since our analysis requires concordance across different product classification systems, we compute weighted average tax rates using similarity scores (Appendix C). We therefore categorize products into intervals [0, 5%], (5%, 12%], (12%, 18%], and >18% to accommodate these derived rates.

¹⁵The estimated coefficients on τ_i^E in the regressions for the counts of products in the GST $\leq 5\%$ and GST $> 18\%$ brackets are 0.27 and -0.124, respectively. Thus, a 0.10 (10 percentage-point) higher effective tax change rate between two plants is associated with roughly 0.027 more products in the GST $\leq 5\%$ category and 0.012 fewer products in the GST $> 18\%$ category for the plant facing the larger tax increase.

Table 3 Impact of GST Reform on Output Portfolio

Variables	(1) Total Number of Outputs	(2) Number of Outputs with GST $\leq 5\%$	(3) Number of Outputs with GST in (5%,12%]	(4) Number of Outputs with GST in (12%,18%]	(5) Number of Outputs with GST >18%	(6) GST Rate of Output Portfolio
Effective Tax Change	0.151** (0.066)	0.270*** (0.034)	0.019 (0.038)	-0.014 (0.044)	-0.124*** (0.018)	-0.038*** (0.003)
\times Post						
ln(Total Number of Workers)	0.098*** (0.011)	0.018*** (0.004)	0.025*** (0.005)	0.049*** (0.007)	0.005** (0.002)	0.000 (0.000)
ln(Gross Assets)	0.001 (0.001)	0.000 (0.000)	0.001 (0.000)	0.001 (0.001)	0.000 (0.000)	0.000 (0.000)
Export Share	0.001*** (0.000)	0.000* (0.000)	0.000*** (0.000)	0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)
Plant FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	277,164	277,164	277,164	277,164	277,164	277,151
R-squared	0.782	0.914	0.834	0.816	0.853	0.948

Notes. This table presents the impact of GST reform on plants' output portfolio. The sample period is 2014/15-2022/23. The dataset for this table is organized at the plant-year-level. The standard errors are reported in parentheses. Standard errors are clustered at the plant level. The *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

6.2. Strategic Reduction in Portfolio Tax Burden

Having documented systematic shifts in the number of products that plants offer across GST tax brackets, we next ask what objective underlies these portfolio adjustments. Our hypothesis is that plants facing larger effective tax increases seek to reduce the average tax burden on their output portfolio. To test this hypothesis, we construct a plant–year measure of the *sales-weighted average GST rate of the output portfolio*. Specifically, we weight each product's GST rate by its share in the plant's gross sales, as shown in Equation (7):

$$PortfolioGST_{it} = \frac{\sum_j GrossSales_{ipt} \times GST_p}{\sum_p GrossSales_{ipt}} \quad (7)$$

where i indexes plants and p indexes products. We apply the GST rate schedule to both pre- and post-GST periods so that changes in this measure reflect shifts in portfolio composition rather than changes in statutory rates. Thus, variation in this variable captures strategic reallocation of production and sales across differently taxed products over time. Appendix Table OA.6 shows an example of the construction of this sales-weighted average GST rate measure for pre- and post-GST periods.

We then estimate how this portfolio GST measure responds to the effective tax change using the model in Equation (4). Column (6) of Table 3 reports the corresponding coefficient. We find that plants facing larger increases in their effective tax change rate (τ^E) significantly reduce the sales-weighted GST rate of their output portfolio, consistent with strategic adjustments in their sales mix. The estimated coefficient is (-0.038), which implies that a 10 percentage-point higher effective tax change rate between two plants is associated with an average portfolio GST rate that

is 0.38 percentage points lower for the plant facing the larger tax increase after the GST reform. This strategic shift toward lower-tax products is not a mechanical response to the tax schedule, but a reaction to changes in relative tax-inclusive prices faced by customers; despite input tax credits, output GST rates still create meaningful tax wedges across products. This pattern, consistent with the product-count evidence in Columns (2)–(5), confirms that plants reconfigure their sales mix to mitigate higher effective tax burdens.

6.3. Parallel Trends and Dynamic Effects

As discussed in Section 5, the parallel trends assumption is central to our DiD specification. To assess both pre-GST parallel trends and the dynamic effects of the reform, we estimate the event-study specification in Equation (5). Figure 3 panels (a)–(e) plot the event-study coefficients for the number of products in each GST rate category and for the sales-weighted average GST rate of the output portfolio. Two patterns stand out. First, the pre-reform coefficients are small and statistically indistinguishable from zero, indicating no systematic differences between plants prior to GST, thereby supporting the parallel trends assumption. Second, following the reform, we observe persistent changes in plants' product mix, particularly for low-tax products (GST ($\leq 5\%$)) and high-tax products (GST ($> 18\%$)). The post-reform coefficients remain shifted relative to the pre-GST baseline, suggesting that GST induces *lasting changes* in output portfolios rather than merely temporary, short-lived adjustments. We find substantial heterogeneity in portfolio responses across industries, with equipment and machinery manufacturing showing the largest adjustments while primary sectors exhibit minimal changes (see Appendix Figure OA.6 for industry-specific estimates).

7. Mechanisms of Portfolio Transformation: Reclassification vs. Reorganization

In the previous section, we show that plants actively reshaped their output portfolios across different GST tax brackets following the reform. While these results reveal the tax-motivated nature of output adjustments, an important question remains: *how* do plants implement these changes in practice, and what kinds of adjustment costs are they willing to bear? Specifically, plants facing higher effective tax increases must balance the incentive to lower tax exposure against the cost of altering established production processes. This trade-off motivates a closer examination at the nature of new products introduced after the reform.

We focus on *new outputs*, defined as the products absent from a plant's pre-reform portfolio but added for the first time after the GST reform.¹⁶ Furthermore, we distinguish between two types of

¹⁶Formally, a product is new for plant i if it is absent from i 's output set in all pre-GST years and appears at least once post-GST.

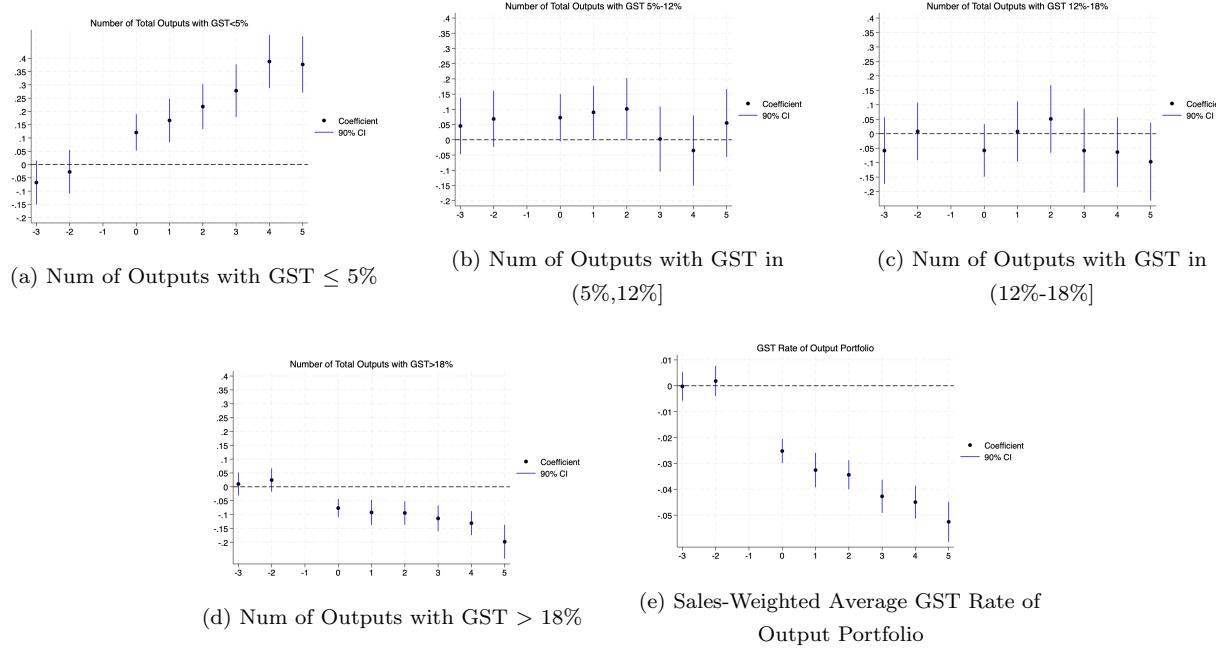


Figure 3 Event Study Estimates for the Number of Products with Varying GST Rate and Portfolio GST Rate

new outputs: (i) reclassified outputs, and (ii) reorganized outputs. Reclassification occurs when the new product closely resembles an existing one in terms of its input composition, but differs in tax code. In this case, the underlying production recipe remains largely unchanged, but the plant can achieve a different tax treatment for the product through marginal modifications, such as dropping or outsourcing a final processing step, rather than fundamentally altering its operations. By contrast, reorganization involves new products with substantially different input portfolios, reflecting genuine changes in the production recipe and deeper operational reconfiguration.

7.1. Examples from Practice

This distinction is particularly salient under the GST, which creates sizable rate differentials between closely related products that share nearly identical production processes. As illustrated in Table 4, milk and cream are taxed at 5%, while ice cream—produced from the same basic inputs but additional light processing—faces an 18% rate. Similarly, bread is taxed at 0–5%, whereas biscuits, which use similar ingredients and baking processes, face an 18% rate. These asymmetries generate a strong incentive for plants to implement minor recipe modifications to qualify for lower-taxed categories.

A prominent example of this operational shift is the transition from dairy-based ice cream to vegetable-fat-based “frozen desserts”. While both products satisfy identical functional demand (for ice-creams) and utilize similar manufacturing infrastructure, substituting dairy fat with vegetable oil allows a firm to reclassify its output into a lower tax bracket. This transition captures the essence



- | | |
|---|--|
| <ul style="list-style-type: none"> • Output: Milk shake mix or soft serve mix • Output value: ₹800 • GST 5%: ₹40 | <ul style="list-style-type: none"> • Input: Milk shake mix or soft serve mix • Output: Ice cream • Output value: ₹1,000 • GST 18%: ₹140
(₹1,000 × 18% - ₹40) |
|---|--|

Figure 4 An illustrative example of value re-distribution via reclassification. Plant A, which previously produced and sold ice cream directly (taxed at 18%), can instead supply milkshake or soft-serve mix classified as “dairy produce” (5% GST) to a downstream Plant B, which completes the ice-cream production and sells the final good. Thus, Plant A’s GST liability falls from ₹180 to ₹40, while Plant B remits the remaining GST on the final output after claiming input credits. The total tax on the final good remains unchanged, but tax liabilities are reallocated along the supply chain, and Plant A’s portfolio becomes concentrated in lower-tax categories.

of reclassification: the plant maintains its core production capabilities but accepts a distorted recipe to minimize the tax wedge.

Figure 4 formalizes the supply chain implications of this strategy. It demonstrates how a plant can redistribute value and tax liabilities by shifting from a finished high-rate good to supplying an intermediate component, such as soft-serve mix (taxed at 5%), to downstream partners. By decomposing the final product in this manner, the plant’s portfolio becomes concentrated in lower-tax categories, effectively defending its operations against the cost shock, albeit at the potential cost of aggregate material productivity.

Table 4 Examples of Minor Product Transformations

Industry	Product Description	GST Rate
Food	Milk and cream	5%
	Ice cream	18%
	Bread	0-5%
	Biscuit	18%
Textile	Fabrics	5%
	Apparel	12%
Metal and machinery	Universal plates of alloy or heat-resisting steel	18%
	Vehicle bodies, air conditioning plants	28%

7.2. Constructing a Product Similarity Measure

To empirically distinguish between reclassification and reorganization, we construct product-level input portfolios and measure product similarity based on material usage. Following Boehm and Oberfield (2020), we build an input–output table from pre-GST input and output data of all the single-output plants in the ASI, which provide clean mappings from inputs to a single output. For each output product, we aggregate across all single-output plants producing that product and

compute input share in total material expenditure, yielding an input portfolio vector V whose elements sum to one. We then measure similarity between any two products a and b using the cosine similarity of their input portfolio vectors:

$$S(a, b) = \cos(V_a, V_b) = \frac{V_a \cdot V_b}{\|V_a\| \|V_b\|},$$

which lies in $[0, 1]$ and captures how closely the two products align in terms of input composition, independent of scale. Let $\mathcal{P}_i^{\text{pre}}$ denote the set of products produced by plant i before the reform, and $\mathcal{P}_i^{\text{new}}$ the set of products that appear only after the reform. For each new product $j \in \mathcal{P}_i^{\text{new}}$, we define its similarity to plant i 's pre-reform portfolio as

$$\text{Sim}_{ij} = \max_{k \in \mathcal{P}_i^{\text{pre}}} S(j, k).$$

A high value of Sim_{ij} indicates that the new product j is closely related to at least one existing product in the plant's portfolio, which is consistent with reclassification. A low value of Sim_{ij} indicates that j is technologically distinct from the plant's pre-reform products, consistent with reorganization. Appendix OA.6 reports an example of the construction of the similarity measure between products. We convert these similarity scores into binary indicators using thresholds of 0.8, 0.85, and 0.9. For a given threshold, new products with scores above the cutoff are deemed as reclassified, while those below are categorized as reorganized. This yields plant–year counts of each type, which we analyze in the next subsection using our continuous DiD framework.

7.3. GST Exposure and Adjustment Strategies

Having defined how we distinguish reclassification from reorganization, we now examine how GST-induced tax exposure tilts plants between these two modes of new product transformation. Specifically, we estimate Equation (4) with counts of reclassified and reorganized new outputs as dependent variables, using thresholds 0.8, 0.85, and 0.9. The results in Table 5 reveal a clear pattern: plants facing higher effective tax increases (τ_i^E) introduce significantly more reclassified new outputs and fewer reorganized ones post-reform. This indicates that greater tax exposure tilts plants' adjustment strategies toward reclassification and away from reorganization. The effect strengthens with product similarity: the coefficient on reclassified products grows from 0.166 to 0.266 as the similarity threshold tightens from 0.8 to 0.9. This gradient effect confirms that the new products introduced by highly exposed plants are not merely similar, but are extremely close counterparts to their existing ones.

These findings are consistent with a resource-conscious response to acute cost pressure. Plants under acute tax strain predominantly rely on reclassification while securing favorable tax treatment. By shifting value to intermediate stages or slightly different output categories, firms can significantly

Table 5 Number of Reclassified and Reorganized New Outputs

Variables	(1) Number of Reclassified New Outputs (0.8)	(2) Number of Reclassified New Outputs (0.85)	(3) Number of Reclassified New Outputs (0.9)	(4) Number of Reorganized New Outputs (0.8)	(5) Number of Reorganized New Outputs (0.85)	(6) Number of Reorganized New Outputs (0.9)
Effective Tax Change	0.166*** (0.030)	0.204*** (0.028)	0.266*** (0.026)	-0.456*** (0.068)	-0.494*** (0.069)	-0.556*** (0.071)
× Post						
Controls	✓	✓	✓	✓	✓	✓
Plant FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	277,164	277,164	277,164	277,164	277,164	277,164
R-squared	0.560	0.558	0.557	0.595	0.597	0.599

Notes. This table presents the impact of GST reform on plants' number of reclassified and reorganized outputs. The sample period is 2014/15-2022/23. The dataset for this table is organized at the plant-year-level. The control variables include log total number of workers, log total asset, and share of exports in total gross sales. The standard errors are reported in parentheses. Standard errors are clustered at the plant level. The *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

reduce their tax liabilities without a fundamental technological overhaul. While the functional demand for the product category may remain stable in the market, the specific product varieties become optimized for tax efficiency rather than pure consumer utility or production excellence.

7.4. Resource Moderation and Adjustment Costs

In this subsection, we first conduct a moderation analysis on whether a plant's resource endowment shifts its response between reclassification and reorganization. We proxy for resource with pre-GST average fixed capital, including the land, building, plant, machinery, and equipment, defined as a time-invariant average value before the GST reform. Table 6 interacts this measure with the treatment intensity. The negative coefficients on the triple interaction term ($EffectiveTaxChange \times Post_t \times Capital$) in the reclassification regressions indicate that capital-intensive plants are *less* likely to cope with tax increases via reclassification. Conversely, the positive triple-interaction coefficients in the reorganization regressions indicate that capital-intensive plants are *more* likely to respond through genuine reorganization of their product mix. Together, these results point to a clear resource-based view of adjustment strategies: smaller, capital-constrained plants facing higher effective tax changes rely on low-cost reclassification, while resource-rich plants can afford the fixed costs of deeper, longer-term reorganization of their product mix.

Next, for the adjustment costs, we examine associations between the two product transformation strategies and post-GST changes in the capital stock of plant and machinery and gross sales-to-material-cost ratio. Appendix Table OA.8 shows the results, which confirm that plants adding more reorganized new outputs are associated with significantly higher capital and material costs than those not adding new outputs. By contrast, plants introducing more reclassified new outputs are not correlated with significant cost increases, underscoring the low fixed-cost nature of reclassification.

Table 6 Moderating Effect of Capital Size on Number of Reclassified and Reorganized New Outputs

Variables	(1) Number of Reclassified New Outputs (0.8)	(2) Number of Reclassified New Outputs (0.85)	(3) Number of Reclassified New Outputs (0.9)	(4) Number of Reorganized New Outputs (0.8)	(5) Number of Reorganized New Outputs (0.85)	(6) Number of Reorganized New Outputs (0.9)
Effective Tax Change	-0.019** (0.009)	-0.024*** (0.008)	-0.031*** (0.008)	0.186*** (0.020)	0.191*** (0.020)	0.198*** (0.021)
\times Post \times Capital						
Effective Tax Change	0.488*** (0.156)	0.604*** (0.148)	0.783*** (0.138)	-3.473*** (0.349)	-3.589*** (0.355)	-3.768*** (0.361)
\times Post						
Capital \times Post	0.002 (0.001)	-0.001 (0.001)	-0.003*** (0.001)	0.033*** (0.002)	0.036*** (0.002)	0.038*** (0.002)
Controls	✓	✓	✓	✓	✓	✓
Plant FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	277,164	277,164	277,164	277,164	277,164	277,164
R-squared	0.560	0.558	0.557	0.597	0.599	0.601

Notes. This table presents the impact of GST reform on plants' number of reclassified and reorganized outputs. The sample period is 2014/15–2022/23. The dataset for this table is organized at the plant-year-level. The moderator *Pre – GST Sales* denotes the log value of pre-GST average gross sales value. The control variables include log total number of workers, log total asset, and share of exports in total gross sales. The standard errors are reported in parentheses. Standard errors are clustered at the plant level. The *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

8. Operational Efficiency Implications of Adjustments

The preceding analysis shows that plants respond to GST-induced tax shocks by reshaping output portfolios in two ways: low-adjustment reclassification of existing products into nearby categories and deeper reorganization into technologically distinct products, especially among larger and more capital-intensive plants. Both types of changes involve adjustment costs, but their implications for production efficiency are ex-ante ambiguous. In principle, reclassification may deliver tax savings with limited disruption to existing recipes, while reorganization may require larger up-front investments, create short-run operational disruption, yet enable new technologies or input combinations.

A natural next step is to ask how these tax-induced portfolio choices affect operational efficiency. Do plants become more efficient overall, or do tax savings and cost adjustments come at the expense of productivity? To study this potential cost–efficiency trade-off, we examine the impact of the GST reform on total factor productivity (TFP), single-factor productivity measures, and plants' input sourcing decisions.

8.1. Estimating Total Factor Productivity

Our primary measure of operational efficiency is total factor productivity (TFP), defined as the amount of output a plant can produce from a given bundle of inputs (Syverson 2011). To measure TFP, we follow Allcott et al. (2016) and estimate a revenue-based Cobb–Douglas production function with three inputs: capital K , labor L , and materials M . Specifically, plant i in year t produces revenue R_{it} according to:

$$R_{it} = \Omega_{it} K_{it}^{\alpha_K} L_{it}^{\alpha_L} M_{it}^{\alpha_M}, \quad (8)$$

where K_{it} is the capital stock, L_{it} is the labor input, M_{it} is the materials input (including goods and energy), and Ω_{it} is the revenue productivity. Plants choose variable inputs to maximize the following static profit:

$$\Pi_{it} = \Omega_{it} K_{it}^{\alpha_K} L_{it}^{\alpha_L} M_{it}^{\alpha_M} - p_L L_{it} - p_M M_{it}, \quad (9)$$

where p_L and p_M denote the prices of labor and materials. Capital costs are treated as predetermined and do not enter the static profit problem.

Estimating Labor and Materials Elasticities: The first-order condition with respect to materials implies

$$\alpha_M \frac{R_{it}}{M_{it}} = p_M \quad \Rightarrow \quad \alpha_M = \frac{p_M M_{it}}{R_{it}}, \quad (10)$$

and analogously, the first-order condition with respect to labor implies

$$\alpha_L \frac{R_{it}}{L_{it}} = p_L \quad \Rightarrow \quad \alpha_L = \frac{p_L L_{it}}{R_{it}}. \quad (11)$$

Under cost minimization, the output elasticities of labor and materials equal their respective revenue shares. We estimate these elasticities using median regressions at the three-digit National Industrial Classification (NIC) industry level, pooling plants within each two-digit NIC group and allowing for year effects and three-digit industry dummies.¹⁷ Specifically, let

$$Y_{it} \in \left\{ \frac{p_M M_{it}}{R_{it}}, \frac{p_L L_{it}}{R_{it}} \right\}$$

denote either the material cost share or the labor cost share. For each two-digit NIC industry, we estimate

$$Y_{it} = \beta_0 + \beta_1 t + \sum_{s=1}^S \beta_{2s} \zeta_{s(i)} + \varepsilon_{it}, \quad (12)$$

where t is a linear time trend (i.e. $t \in \{1, 2, \dots, T\}$), $s(i)$ denotes the three-digit NIC industry of plant i , and $\zeta_{s(i)}$ are three-digit NIC industry dummies. We estimate the median regression coefficients $\beta = (\beta_0, \beta_1, \beta_{2s})$ separately for each two-digit industry. We then recover industry-year-specific elasticities $\hat{\alpha}_M$ and $\hat{\alpha}_L$ for three-digit NIC industry s in year t by summing the appropriate intercept, time effect, and industry effect:

$$\hat{\alpha}_{M,st} = \hat{\beta}_0^{(M)} + \hat{\beta}_1^{(M)} \cdot t + \hat{\beta}_{2s}^{(M)}, \quad \hat{\alpha}_{L,st} = \hat{\beta}_0^{(L)} + \hat{\beta}_1^{(L)} \cdot t + \hat{\beta}_{2s}^{(L)}.$$

¹⁷We estimate equation (12) separately for each two-digit NIC industry and include three-digit NIC dummies within that group. This pooling exploits the fact that three-digit industries within a two-digit sector share similar technologies, while the dummies $\zeta_{s(i)}$ allow for different average cost shares across three-digit industries. The fitted values then deliver industry year elasticities at the three-digit level, with the time profile identified from variation within the broader two-digit group.

Estimating Capital Elasticity and Constructing TFP: Capital is subject to adjustment costs, so the static first-order condition does not identify α_K . Following Allcott et al. (2016), we estimate the capital elasticity using a control-function approach. Taking logs of Equation (8) yields

$$r_{it} = \alpha_K k_{it} + \alpha_L l_{it} + \alpha_M m_{it} + \omega_{it} + \nu_{it}, \quad (13)$$

where lowercase letters denote logs, ω_{it} is (log) TFP, and ν_{it} is an idiosyncratic revenue shock. Using the estimated labor and materials elasticities, we define the transformed revenue as

$$\tilde{r}_{it} \equiv r_{it} - \hat{\alpha}_L l_{it} - \hat{\alpha}_M m_{it} = \alpha_K k_{it} + \omega_{it} + \nu_{it}. \quad (14)$$

A naive OLS regression of \tilde{r}_{it} on k_{it} would suffer from endogeneity because more productive plants tend to choose higher capital ($E[\omega_{it}k_{it}] \neq 0$). To address this, we adopt a control-function framework under the following standard assumptions:

Assumption 1 (Investment function). *Investment is a strictly monotone function of capital and productivity, $I_{it} = I(K_{it}, \omega_{it})$.*

Assumption 2 (Capital accumulation). *Capital evolves according to*

$$K_{it} = (1 - \kappa)K_{i,t-1} + I_{i,t-1},$$

where κ is the depreciation rate.

Assumption 3 (Productivity dynamics). *Productivity follows a first-order Markov process*

$$\omega_{it} = g(\omega_{i,t-1}) + \xi_{it},$$

where $g(\cdot)$ captures persistence and ξ_{it} is an innovation uncorrelated with past inputs.

Under these assumptions, the current capital k_{it} is determined by past states and investment, so the innovation ξ_{it} is orthogonal to k_{it} , i.e., $E[\xi_{it}k_{it}] = 0$. We use this moment condition to estimate α_K from Equation (14) via GMM, with bootstrapped standard errors. We construct the necessary plant-level variables from the ASI: gross sales, employment, net fixed assets, and purchase values of materials and energy, all deflated using a state–year price index from Agrawal and Zimmermann (2025). Given the estimated input elasticities ($\hat{\alpha}_K, \hat{\alpha}_L, \hat{\alpha}_M$), we compute plant-level TFP as the residual from Equation (13):

$$\hat{\omega}_{it} = r_{it} - \hat{\alpha}_K k_{it} - \hat{\alpha}_L l_{it} - \hat{\alpha}_M m_{it}. \quad (15)$$

Table 7 reports summary statistics for the estimated production-function coefficients across industries and years. The mean elasticities are 0.105 for labor, 0.687 for materials, and 0.135 for capital, consistent with the high materials intensity of manufacturing production.

Table 7 Production Function Parameter Estimates and TFP

	Number of Coefficients	Mean	25 Percentile	75 Percentile
	(1)	(2)	(3)	(4)
Labor (α_L)	759	0.105	0.066	0.133
Materials (α_M)	759	0.687	0.613	0.767
Capital (α_K)	759	0.135	0.087	0.187
Measured TFP (ω_{it})	451,996	3.010	2.158	3.717

Notes: Distribution statistics for production function coefficients and returns to scale are based on 759 three-digit NIC industry-by-year observations. Distribution statistics for measured TFP are based on 451,996 plant-year observations.

8.2. Productivity Declines and Input Sourcing Shifts

Having estimated TFP, we now quantify the impact of the GST reform on plants' overall production efficiency and the underlying single-factor productivity measures (output per unit of labor, materials, and capital). We then examine input sourcing decisions that may underlie the observed productivity changes.

Our analysis reveals a puzzling pattern: plants facing larger effective tax increases experience a significant decline in total factor productivity (TFP). Table 8 reports the impact of the GST reform on productivity outcomes using Equation (4). The coefficient on $EffectiveTaxChange \times Post_t$ in Column (1) is -0.222 , so a 0.1 (10 percentage-point) higher effective tax increase is associated with about a 0.022 log-point, or 2.2 percent, reduction in TFP. This result indicates that tax hikes reduce aggregate production efficiency on average: plants with higher effective tax changes require more inputs to produce the same level of output.

Table 8 Impact of GST Reform on Productivity

Variables	(1) ln(TFP)	(2) ln(Gross Sales/Labor Cost)	(3) ln(Gross Sales/Number of Employees)	(4) ln(Gross Sales/Material Cost)	(5) ln(Gross Sales/Capital Stock)
Effective Tax Change \times Post	-0.222*** (0.049)	0.472*** (0.061)	0.488*** (0.062)	-0.096*** (0.027)	0.418*** (0.144)
Controls	✓	✓	✓	✓	✓
Plant FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Observations	273,830	275,557	275,557	274,860	275,557
R-squared	0.957	0.857	0.893	0.724	0.712

Notes: This table presents the impact of GST reform on firms' productivity. The sample period is 2014/15-2022/23. The dataset for this table is organized at the firm-year-level. The control variables include log total number of workers, log total asset, and share of exports in total gross sales. The standard errors are reported in parentheses. Standard errors are clustered at the firm level. The *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

To unpack this TFP decline, we first examine the production function elasticities and find that they are quite stable over time (see Appendix Figure OA.7). Given our definition of TFP: $\hat{\omega}_{it} = r_{it} - \hat{\alpha}_K k_{it} - \hat{\alpha}_L l_{it} - \hat{\alpha}_M m_{it}$, the decline in TFP must therefore come from the way revenue and input quantities respond to the tax shock, rather than from changes in the elasticities.

Columns (2)–(5) of Table 8 use single-factor productivity measures to unpack these responses. Plants subject to larger effective tax increases exhibit significant gains in labor productivity (measured as gross sales per unit of labor cost and per worker (Columns 2 and 3)) as well as higher capital productivity (Column 5). This pattern suggests that plants implement operational adjustments that use labor and capital more intensively as a defensive response to increased tax pressure. At the same time, Column (4) shows that gross sales per unit of material cost decline significantly for more exposed plants, implying that material inputs grow faster than revenue.

The TFP estimates in Column (1), which synthesize all three inputs, reveal a net decline in operational efficiency: a 10 percentage-point increase in the effective tax rate corresponds to a 2.2 percent reduction in post-reform TFP. Given that material productivity is the only single-factor measure to deteriorate, these findings suggest that GST-induced tax shocks drive plants toward more material-intensive production, outweighing the observed gains in labor and capital efficiency.

To further investigate the decline in material productivity, we use Equation (4) to examine how GST affects the total cost of materials and its components: domestic inputs, imported inputs, and energy. We include $\ln(\text{GrossSales}_{it})$ as a control to account for output scale. Table 9 presents the results. Column (1) shows that plants facing larger effective tax changes experience a significant increase in total material costs, holding gross sales constant. Columns (2)–(4) reveal that this increase is driven entirely by a compositional shift in material spending: domestic material costs rise sharply (Column (2)), imported material costs fall substantially (Column (3)), and energy costs change little (Column (4)).¹⁸

Table 9 Impact of GST Reform on Material Costs

Variables	(1) $\ln(\text{Total Cost of Materials})$	(2) $\ln(\text{Cost of Domestic Items})$	(3) $\ln(\text{Cost of Imported Items})$	(4) $\ln(\text{Cost of Energy Input})$
Effective Tax Change × Post	0.125*** (0.027) (0.004)	0.337*** (0.077) (0.008)	-1.258*** (0.296) (0.024)	0.010 (0.055) (0.006)
Controls	✓	✓	✓	✓
Plant FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Observations	274,860	275,274	275,274	275,143
R-squared	0.992	0.921	0.798	0.961

Notes: This table presents the impact of GST reform on plants' material costs. The sample period is 2014/15–2022/23. The dataset for this table is organized at the plant-year-level. The control variables include log total number of workers, log total asset, share of exports in total gross sales, and gross sales. The standard errors are reported in parentheses. Standard errors are clustered at the firm level. The *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

¹⁸For a 10 percentage-point increase in the effective tax rate change, the coefficient in Column (1) implies approximately a 1.3 percent increase in total material costs. The coefficients in Columns (2)–(4) imply approximately a 3.4 percent increase in domestic material costs, a 12.6 percent decrease in imported material costs, and a negligible 0.1 percent change in energy costs. Since domestic materials account for approximately 81 percent of total material spending in our sample, the increase in domestic costs more than offsets the decline in imported costs.

Input Sourcing Shifts: To investigate the rise in domestic material costs, we use a plant-input item-year-level panel and decompose the purchase value of domestic inputs into quantity and unit price. We estimate the following specification:

$$y_{ikt} = \beta_0 + \beta_1 \tau_i^E \times Post_t + \phi' X_{it} + \lambda_i \times \theta_k + \gamma_t + \epsilon_{ikt}, \quad (16)$$

where i denotes the plant, k denotes the specific input item, and t denotes the year. This model includes plant-by-input fixed effects to control for time-invariant sourcing preferences. Table 10 shows the results. Column (1) reveals that plants facing higher effective tax increases significantly expand the quantity of existing domestic inputs. In contrast, Column (2) indicates a modest decrease in average unit prices. This pattern suggests that the rise in domestic procurement costs is primarily driven by quantity increases rather than price hikes.

Table 10 Impact of GST Reform on Domestic Material Cost Decomposition (Quantity and Price)

Variables	(1) ln(Quantity)	(2) ln(Price)
Effective Tax	0.348*** (0.080)	-0.090* (0.054)
Change × Post		
ln(Gross Sales)	0.839*** (0.007)	0.024*** (0.004)
Controls	✓	✓
Plant × Item FE	✓	✓
Year FE	✓	✓
Observations	957,690	957,487
R-squared	0.955	0.970

Notes: This table presents the impact of GST reform on firms' existing material costs. The sample period is 2014/15-2022/23. The dataset for this table is organized at the firm-input item-year-level. The control variables include log total number of workers, log total asset, and share of exports in total gross sales. The standard errors are reported in parentheses. Standard errors are clustered at the firm level. The *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

One plausible interpretation is that the expansion of domestic sourcing is driven by GST's structural changes, specifically the seamless flow of Input Tax Credits (ITC) and the reduction in interstate trade frictions, which make domestic procurement more attractive relative to imports. However, as plants substitute away from high-quality imported intermediates toward a broader set of domestic suppliers, they often shift to cheaper, lower-grade varieties with higher defect/waste rates and inconsistency. Consequently, these plants require more physical units to achieve the same output, explaining the material productivity decline. These sourcing adjustments help rationalize the observed decline in material productivity: while plants successfully defend their operations by reorganizing their input mix to leverage tax benefits, the resulting increase in materials intensity relative to output ultimately leads to a drop in aggregate productivity.

Our analyses of product portfolios, input sourcing, and productivity highlight a tension: plants with larger tax increases shift their output mix toward lower GST slabs and input sourcing from imported to domestic materials, in order to mitigate costs, but this adjustment creates a more

material-intensive production process. Consequently, material productivity falls and overall TFP declines, despite labor and capital productivity improving. This reveals a cost-efficiency trade-off where tax-motivated adjustments reduce productivity through heavier materials use. Appendix OA.9 formalizes this trade-off in a model of firm response to tax shocks.

9. Working Capital Management: Inventory Productivity Gains

Building on the previous finding that higher effective tax rates reduce Total Factor Productivity (TFP) and material efficiency, we now investigate the financial channel of working-capital constraints. Because GST on inputs must be paid upfront, effectively locking up cash until credits can be claimed against output sales, higher effective rates increase the shadow cost of holding inventory. This liquidity pressure creates an incentive for plants to tighten working-capital discipline and accelerate turnover, particularly for work-in-process and finished goods.

This section examines inventory productivity as a complementary dimension of operational performance and a lever for freeing up capital under fiscal pressure. We study whether plants facing larger tax increases respond by tightening inventories across raw materials, work-in-process, and finished goods, and how these adjustments fit into the broader trade-off between tax-induced costs and production efficiency.

9.1. Measures of Inventory Productivity

The standard measure of inventory productivity is inventory turnover, defined as the ratio of the cost of goods sold (COGS) to average inventory. It captures how efficiently a plant converts inventory into sales. We distinguish between the three inventory stages in the manufacturing process (raw materials, work-in-process (WIP), and finished goods) which differ in how easily managers can adjust them (Rajagopalan and Malhotra 2001). WIP inventory is most directly under internal production control and is a primary target of lean initiatives such as just-in-time production and cycle-time reduction. Finished-goods inventories are constrained by customer-service requirements and demand uncertainty, while raw-material inventories are affected by supplier contracts, minimum order quantities, and delivery lead times, all of which limit how much plants can optimize them based purely on internal decisions.

To study each stage, we compute inventory turnover separately for raw materials, WIP, and finished goods following Rajagopalan and Malhotra (2001). For plant i in year t , let MaterialCost_{it} denote the cost of raw materials, COGS_{it} the cost of goods sold, and $\text{ValueAdded}_{it} = \text{COGS}_{it} - \text{MaterialCost}_{it}$ the value added. Let InvRaw_{it} , InvWIP_{it} , and InvFin_{it} be the raw-material, WIP, and finished-goods inventories, respectively. We define inventory turnover for each type as:

$$\text{ITR}_{\text{Raw},it} = \frac{\text{MaterialCost}_{it}}{\text{InvRaw}_{it}}, \quad (17)$$

$$\text{ITWIP}_{it} = \frac{\text{MaterialCost}_{it} + 0.5 \times \text{ValueAdded}_{it}}{\text{InvWIP}_{it}}, \quad (18)$$

$$\text{ITFin}_{it} = \frac{\text{COGS}_{it}}{\text{InvFin}_{it}}. \quad (19)$$

We note here that raw inventory turnover varies widely across plants and over time, which limits its usefulness as a metric for performance comparison and working-capital management, since it mechanically reflects differences in product mix, gross margins, capital intensity, and demand shocks (Gaur et al. 2005). To obtain a cleaner measure of inventory management, we construct adjusted inventory turnover (AIT) for each inventory type after controlling for these factors following Gaur et al. (2005) and Agrawal and Osadchiy (2024). Let Sale_{it} denote net sales, GFA_{it} gross fixed assets, and Inv_{it} total inventory (the sum of raw materials, WIP, and finished goods). We define gross margin, capital intensity, and sales surprise as:

$$\text{GM}_{it} = \frac{\text{Sale}_{it} - \text{COGS}_{it}}{\text{Sale}_{it}}, \quad (20)$$

$$\text{CI}_{it} = \frac{\text{GFA}_{it}}{\text{Inv}_{it} + \text{GFA}_{it}}, \quad (21)$$

$$\text{SS}_{it} = \frac{\text{Sale}_{it}}{\text{Sale}_{it-1}}. \quad (22)$$

We calculate AIT following the procedure outlined by Gaur et al. (2005). For notational convenience, let $\text{IT}_{it} \in \{\text{ITRaw}_{it}, \text{ITWIP}_{it}, \text{ITFin}_{it}\}$ denote inventory turnover for raw materials, WIP, or finished goods, respectively. We estimate the following regression separately for raw materials, WIP, and finished goods:

$$\ln \text{IT}_{it} = \lambda_i + \gamma_t + b_1 \ln \text{GM}_{it} + b_2 \ln \text{CI}_{it} + b_3 \ln \text{SS}_{it} + e_{it}. \quad (23)$$

where λ_i and γ_t are plant and year fixed effects. Then, using the estimated coefficients, we compute adjusted inventory turnover as:

$$\text{AIT}_{it} = \text{IT}_{it} \text{GM}_{it}^{-b_1} \text{CI}_{it}^{-b_2} \text{SS}_{it}^{-b_3}, \quad (24)$$

Higher AIT_{it} indicates more efficient inventory management after controlling for differences in margins, capital intensity, and sales shocks.

9.2. Impact of GST on Various Inventory Productivity

We estimate GST's impact on inventory productivity using our baseline specification in Equation (4) and replacing the dependent variable with $\ln(\text{AIT}_{it})$ for each inventory type. Table 11 reports the results. For raw-material inventories, Column (1) shows that the effect of *Effective Tax Change* \times *Post* on adjusted inventory turnover is positive but relatively small. Thus, plants facing larger tax increases somewhat enhance their raw-material turnover. In contrast, Columns (2)–(3) reveal

Table 11 Impact of GST Reform on Inventory Productivity

Variables	(1) ln(AIT) (Raw Material)	(2) ln(AIT) (WIP)	(3) ln(AIT) (Finished Goods)
Effective Tax Change × Post	0.121* (0.063)	0.287*** (0.079)	0.229*** (0.079)
Controls	✓	✓	✓
Plant FE	✓	✓	✓
Year FE	✓	✓	✓
Observations	212,989	119,072	183,363
R-squared	0.834	0.865	0.832

Notes. This table presents the impact of GST reform on firms' inventory productivity. The sample period is 2014/15-2022/23. The dataset for this table is organized at the plant-year-level. The control variables include log total number of workers, log total asset, and share of exports in total gross sales. The standard errors are reported in parentheses. Standard errors are clustered at the firm level. The *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

more pronounced responses for work-in-process (WIP) and finished-goods inventories. Plants facing higher effective tax increases significantly raise adjusted turnover for both categories, generating equivalent sales with leaner stocks. This shift also improves liquidity by freeing working capital and reducing inventory holding costs.

This positive effect is highest for WIP, followed by finished goods, with raw materials showing the smallest improvement. This pattern is consistent with differential adjustment flexibility across inventory stages. WIP inventories are most directly under internal production control, so plants can streamline in-process buffers and cycle times in response to tax pressure. Finished-goods inventories respond more moderately, reflecting a balance between tighter internal operations and customer-service and demand-uncertainty constraints. Raw-material inventories show the smallest efficiency gains, in line with the upstream contractual and lead-time frictions discussed in Section 9.1.

More importantly, these inventory productivity gains complement our productivity findings in Section 8.2. Plants facing larger effective tax increases become less efficient in transforming inputs into output, as TFP and material productivity decline when they substitute toward more materials-intensive domestic intermediates, yet they simultaneously improve the efficiency with which they manage WIP and finished-goods inventories. Taken together, these results show how inventory adjustments fit into the broader cost–efficiency trade-off: GST-induced tax shocks lead plants to trade lower production efficiency for tighter working-capital management, becoming leaner in WIP and finished-goods inventories while production becomes more materials intensive.

Robustness Analyses: First, our results hold across alternative values of the cascading factor α (ranging from 0.25 to 0.5) used to construct the effective tax change measure. Second, results remain consistent when using discrete treatment categories rather than continuous treatment intensity. Third, placebo tests with randomly reassigned treatment show that our estimated effects lie well outside the distribution of placebo coefficients, confirming they are unlikely to arise from chance.

Finally, we obtain consistent productivity results using Data Envelopment Analysis (DEA) as an alternative non-parametric efficiency measure. Full details of all robustness checks are provided in Online Appendix OA.8.

A Simple Theoretical Model of Cost Shocks and Production Reorganization: To formalize the empirical results, we develop a simple model in which a plant facing a tax shock can (i) absorb the shock and maintain its original product, (ii) reclassify its product into a lower tax slab through minor modifications that involve low fixed costs but may reduce efficiency, or (iii) reorganize production more deeply, adopting a new technology or product line that requires larger fixed investment and also affects efficiency. The model shows that the optimal choice depends on the tax shock magnitude and plant scale. Small plants facing intermediate shocks prefer reclassification because they cannot justify the higher fixed costs of reorganization relative to their output; large plants facing substantial shocks can spread reorganization's fixed costs over more units, making deeper restructuring viable. The model's predictions align with our empirical findings: plant size and tax shock magnitude jointly determine adjustment strategies. The formal model and proofs are in Online Appendix OA.9.

10. Discussion and Conclusion

Our study advances the operations management literature by providing granular empirical evidence on how regulatory cost shocks drive internal operational restructuring, moving beyond the “firm-as-black-box” perspective to reveal the micro-level trade-offs between cost minimization and production efficiency. Leveraging India’s 2017 Goods and Services Tax (GST) reform as a natural experiment, we exploit heterogeneous effective tax changes across plants to identify a novel “quantity-for-quality” substitution channel: as plants substitute toward cheaper domestic inputs to mitigate cost burdens, they often shift to lower-grade varieties. This transition introduces higher defect rates and physical waste, forcing plants to use more units to maintain output levels—a process that rationalizes the observed 2.2% decline in TFP for every 10-percentage-point tax increase.

A key contribution is our distinction between low-cost *reclassification*—minor recipe changes favored by resource-constrained plants—and fundamental *reorganization*, where larger, capital-intensive firms undertake deeper operational restructuring despite higher upfront costs. By developing a novel measure of product similarity based on input composition, we show that large exogenous shocks—whether from carbon pricing, shifting tariffs, or geopolitical fragmentation—reshape not only what firms sell, but their production recipes, input sourcing, and efficiency outcomes. Resource endowment emerges as a critical moderator: constrained plants prioritize incremental, low-fixed-cost adjustments that preserve capabilities but limit long-run gains, while resource-rich plants invest in transformative changes for potentially superior performance.

These findings offer a cautionary tale for both managers and policymakers regarding the hidden costs of financial hedging strategies. For managers, our results underscore that quick, low-cost fixes like reclassification may offer immediate tax savings but entail lasting productivity losses; long-term resilience requires weighing these immediate gains against the erosion of operational efficiency. For policymakers, our evidence reveals the unintended consequences of heterogeneous reforms: large, uneven cost shocks can induce the widespread adoption of efficiency-reducing strategies, especially among smaller firms, suggesting that transition support or targeted aid for resource-constrained entities could mitigate productivity losses while preserving the policy goals of tax unification. Overall, this study illuminates a fundamental tension in operations management—balancing cost containment against operational stability—that extends beyond tax policy to diverse regulatory and supply chain pressures.

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Online Appendix: “Navigating Cost Shocks: Evidence on Production Reorganization from the GST Reform in India”

OA.1. Institutional Details of GST Reform

Structure of Pre-GST Taxes Appendix Table OA.1 presents India’s tax structure before the GST reform, which was primarily divided into central taxes and state taxes. Each category contained multiple tax subcategories, creating an overall highly complex system. The GST reform consolidated numerous tax categories and simplified the tax rate structure.

Table OA.1 Structure of Central and State Taxes in India before GST

CENTRAL TAXES	
1. Central value-added tax (CENVAT) or Central Excise duty	<i>Tax levied on the production of manufacturing goods.</i>
2. Service Tax	<i>Tax levied on provided services.</i>
3. Central Sales Tax (CST)	<i>Tax on cross-state trade.</i>
4. Countervailing Duties (CVD)	<i>Additional import duty on imported goods produced in India to ‘level the playing field’ between domestic and foreign producers. Additional CVDs might be applied to offset the effect of concessions and subsidies granted by an exporting country to its exporters.</i>
5. Special Additional Duty of Customs (SAD)	<i>Additional import duty to counterbalance the sales or value-added tax payable by local manufacturers.</i>
STATE TAXES	
1. Value-added tax (VAT)	<i>Tax levied on the production of manufacturing goods.</i>
2. Sales Tax	<i>Additional tax levied on the production of manufacturing goods. It was replaced in most states by VAT, but not all.</i>
3. Entry Tax	<i>Tax on the entry of goods for consumption, use or sale in that state.</i>
4. Luxury Tax	<i>Tax on luxury goods and services that include hotels, resorts, and congregational halls used for weddings, conferences, etc.</i>
5. Entertainment Tax	<i>Tax on feature films, major commercial shows and private festivals.</i>

Source: Van Leemput and Wienczek (2017)

Tax Cascading in Pre-GST System Ahmad and Poddar (2009) provide details of tax cascading in the pre-GST tax system. One contributing factor to tax cascading is partial coverage under both CENVAT and state VAT. For example, the exempt sectors are not allowed to claim any input credits for the CENVAT and state VAT, including the entire service sector, real property sector, agriculture, oil and gas production, and mining. Another contributing factor is the CST on inter-state sales, collected by the origin state, for which no credit is allowed by any level of government.

An Example on the Complexity of Pre-GST Taxes across the Supply Chain In this example, the excise duty is paid to the government and VAT is paid to the respective state governments.

- Manufacturer 1 (State A) produces a product of value ₹1000 and pays excise duty (10%, ₹100) and VAT (5%, ₹50).
- Manufacturer 2 (State A) adds ₹500 in value and pays excise duty of ₹150, claiming input credit of ₹100 and paying ₹50. If goods are sold within the state, VAT is charged with a ₹50 input credit. But for inter-state sales to Manufacturer 3, CST (2%, ₹30) and entry tax (5%, ₹75) are applied, with no credit available.

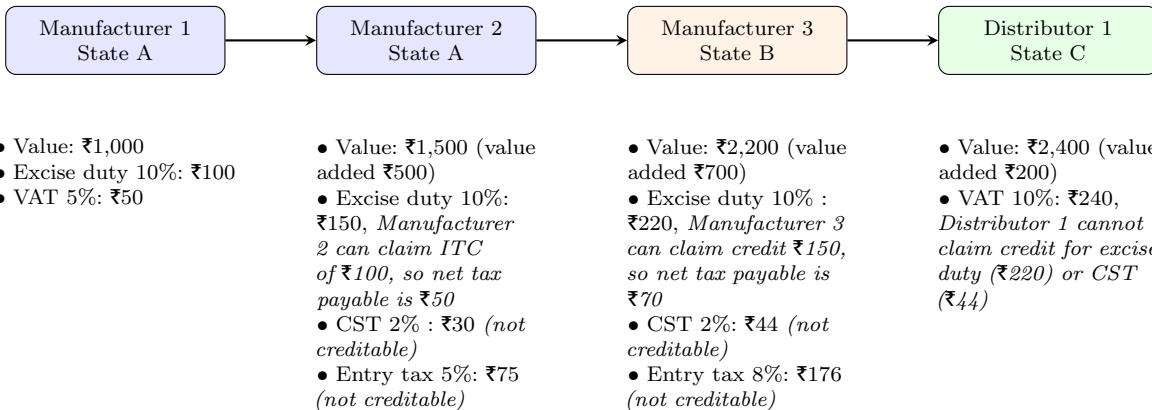


Figure OA.1 An Illustrative Example Showing the Complexity of Pre-GST Taxes in the Supply Chain

- Manufacturer 3 (State B) adds ₹700 in value, pays excise duty of ₹220 (with ₹150 credit), and again incurs non-creditable CST (₹44) and entry tax (8%, ₹176) when selling to Distributor 1 (State C).
- Distributor 1 (State C) charges VAT (10%, ₹240) on intra-state sales. However, no credit is allowed for the CST (₹44) or excise duty (₹220), amplifying the tax burden.

This example highlights the complexity and inefficiency of the pre-GST regime. Multiple taxes with varying rates across states and products, combined with limited credit mechanisms, resulted in cumulative taxation. Each firm in the chain paid taxes on amounts that included previously taxed values, inflating final prices.¹⁹

Key Characteristics of GST System

- One Nation, One Tax: GST replaced multiple indirect taxes levied by the Central and State Governments, such as excise duty, service tax, value-added tax (VAT), and others. It brought uniformity in the tax structure across India, eliminating the cascading effect of taxes.
- Input Tax Credit (ITC): Firms can claim credit for taxes paid on inputs, avoiding double taxation.
- Threshold exemption: Small businesses below a specified turnover threshold are exempt from GST, easing compliance burdens.
- Composition scheme: It is a simplified GST payment scheme for small taxpayers with an annual turnover below a specified limit.
- Benefits for exporters: No GST is charged on the final exported product or service, and exporters can claim a refund of GST paid on inputs.

OA.2. ASI Sampling Design and Data Processing

Content and data sampling method. Annual Survey of Industries (ASI) serves as India's primary source of industrial statistics, providing comprehensive data on the manufacturing sector. The survey has so far been conducted annually under the statutory provisions of the Collection of Statistics (COS) Act. As a statutory survey, ASI requires units/entrepreneurs to submit returns, balance sheets, and other relevant documents

¹⁹While intra-state VAT partly addressed cascading, significant problems remained due to delayed crediting of central excise (CENVAT), exclusion of major sectors from CENVAT, denial of VAT credit in those sectors, and the inability to credit CST on inter-state trade (Keen 2014).

within the prescribed period after receiving the notice. Failure to comply may result in penalties under the COS Act.

The ASI employs a stratified sampling design with two primary components: Census and Sample schemes. The Census scheme mandatorily surveys all units in less industrially developed states/UTs, salt extraction units, establishments above specific employment thresholds (varying by state from 50 to 100 employees), joint returns, and strata with four or fewer units. The remaining units are covered under the Sample scheme, where strata are formed based on State \times District \times Sector (bidi, factory, or electricity) \times three-digit NIC-2008 classification. Within each stratum, units are arranged in descending order of their total number of employees, and a minimum of four units are selected using Circular Systematic Sampling, considering an overall sampling fraction (about 16% to 22%).

To ensure data representativeness, the ASI annually assigns sample weights (multipliers) to each surveyed factory. The sample weights are calculated as E_{is}/e_{is} , where i denotes state, s denotes stratum, E_{is} denotes the total number of factories in the sample scheme in a stratum, and e_{is} denotes the number of factories surveyed out of the total number of factories in the sample scheme in a stratum. By design, factories under the census scheme receive a sample weight of one, while those under the sample scheme receive weights greater than one. When estimating characteristics of the total population, sample weights are essential for statistical inference. These weights ensure that the observations in each survey year are representative of the total population of manufacturing factories registered under the Factories Act. In all the regressions, we apply sample weights using each plant's multiplier, which record the number of units in the full population that each sampled observation represents Agrawal and Zimmermann (2025). This approach implements weighted least squares, where each plant's contribution to the objective function is proportional to its multiplier value – effectively allowing sampled plants to represent unsampled plants with similar characteristics. Plants in the census scheme (multiplier=1) receive standard weight, while those in the sample scheme receive weights equal to their sampling multipliers, ensuring our estimates are representative of the full population of Indian plants rather than just the sampled units.

Coverage. The ASI provides comprehensive national coverage of India's manufacturing sector, using factories as its primary unit of enumeration. Figure (a) of Appendix Figure OA.2 shows the number of factories by scheme over time. The ASI surveys over 50,000 factories each year. Except for 2014-15, the number of factories under the Census scheme consistently exceeds those under the Sample scheme. Over the years, the number of factories covered under the Census scheme has steadily increased, while those under the Sample scheme have shown a declining trend.

Coverage varies by industry and state. Figure (b) of Appendix Figure OA.2 reports the number of factories during the sample periods by high-level aggregation of NIC industry codes. The food sector contains the largest share of factories in our data, followed by chemicals and plastics/rubbers, metals, and textiles. Figure (c) of Appendix Figure OA.2 shows the number of factories across Indian states and union territories. Tamil Nadu leads with 9,289 factories, followed by Maharashtra (8,473), Gujarat (7,309), and Uttar Pradesh (5,862). This distribution largely reflects India's uneven industrial development, where states with better infrastructure

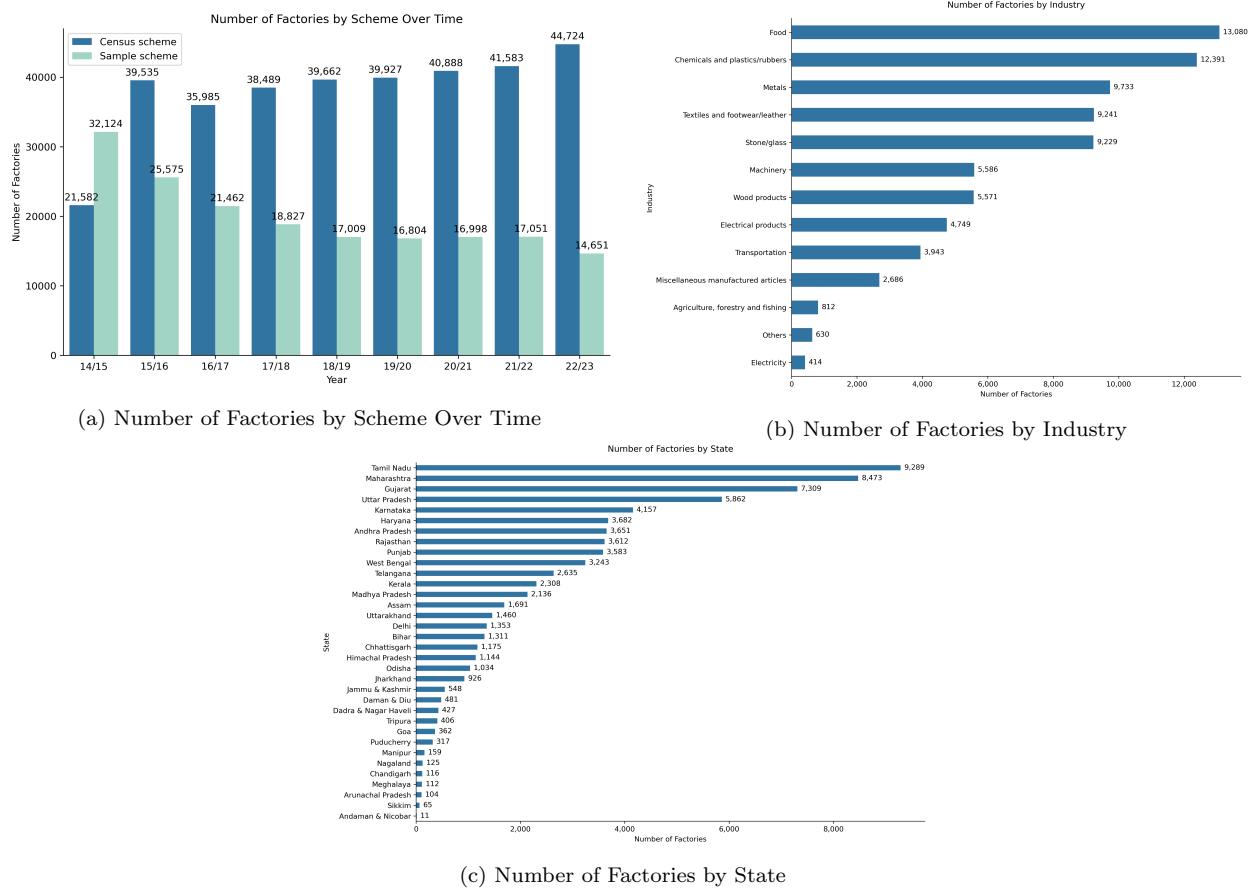


Figure OA.2 Summary Statistics of ASI Data

and historical industrial bases maintain their manufacturing advantage, while traditionally agricultural or remote regions show limited industrial presence.

Key variables. Appendix Table OA.2 shows the key variables from different blocks of the ASI schedule. Blocks A and B contain basic factory information. Block C covers fixed assets across various asset categories, and Block D contains working capital and loans. Block E details employment and labor costs, Block F records other expenses, and Block G documents other outputs and receipts. Blocks H and I, respectively, capture indigenous and imported input items consumed. Block J contains information on manufactured products and by-products.

OA.3. Key Variable Construction and Model Free Evidence

Construction of Key Variables Section 4.2 describes the construction of our key variables. We provide a practical example showing how we derive output tax change rate, pre-GST input tax rate, and effective tax change rate, as illustrated in Appendix Table OA.3. We first calculate the output tax change rate (τ_i^O) as the difference between pre-GST taxes (central excise duty plus VAT) and post-GST rates, weighted by each output's sales share. For inputs, we compute the pre-GST input tax rate ($\tau_i^{I,Pre}$) as the weighted average of pre-tax rates across input items. Finally, we derive the effective tax change rate (τ_i^E) by accounting for both

Table OA.2 Key Variables in ASI Data

Blocks	Key Variables
Block A: Identification particulars	factory ID, scheme code (census-1, sample-2), industry code (NIC-2008), sector (rural-1, urban-2), number of units, status of unit, bonus, workman & staff welfare expenses, number of working days (manufacturing, non-manufacturing, and total), total cost of production, share percentage of directly exported products/by-products.
Block B: Particulars of the factory	type of organization, year of initial production, accounting year period (from and to dates), number of months of operation, share capital participation of foreign entities (yes-1, no-2), R&D unit status, and formal training provision status.
Block C: Fixed assets (the types of assets include land, building, plant & machinery, transport equipment, computer equipment, pollution control equipment)	gross value opening, gross value addition due to revaluation, actual additions, deductions & adjustments during the year, gross value closing, depreciation provided up to year beginning, depreciation provided during the year, depreciation adjustments for sold/discharged items, depreciation up to year end, net value opening, and net value closing.
Block D: Working capital and loans	opening and closing values of inventories of raw materials & components and packing materials, fuels & lubricants, spares, stores & others, semi-finished goods/work-in-progress, finished goods, current assets including cash in hand and at bank, sundry debtors, current liabilities including sundry creditors, over draft, cash credit, other short term loan from banks & other financial institutions.
Block E: Employment and labor cost (the categories of staff include male and female workers, contract workers, managerial staff, family members)	mandays worked for manufacturing and non-manufacturing activities, total mandays worked, average number of persons worked, number of mandays paid for, and wages/salaries.
Block F: Other expenses	work done by others on materials supplied, repair & maintenance of buildings and other construction, repair & maintenance of other fixed assets, operating expenses, expenses on raw materials for own construction, insurance charges, rent paid for plant & machinery and other fixed assets, R&D expenses, rent paid for buildings, rent paid for land lease or royalties on mines/quarries, interest paid, purchase value of goods sold in same condition, and inward/outward transportation costs (available after 2018).
Block G: Other output/receipts	receipts from manufacturing services (including work done for others), receipts from non-manufacturing services, value of electricity generated and sold, value of own construction, net balance of goods sold in same condition, rent received for plant & machinery and fixed assets, variation in stock of semi-finished goods, rent received for buildings, rent received for land lease or royalties, interest received, sale value of goods sold in same condition, and other production subsidies.
Block H: Indigenous input items consumed (item types include basic items, non-basic chemicals, packing items, electricity, and fuel)	item code (NPCMS), unit of quantity code, quantity consumed, purchase value, and rate per unit.
Block I: Imported input items consumed	item code (NPCMS), unit of quantity code, quantity consumed, purchase value, and rate per unit.
Block J: Products and by-products manufactured by the unit	item code (NPCMS), unit of quantity code, quantity manufactured, quantity sold, gross sale value, charges, subsidies, per unit net sale value, and ex-factory value of quantity manufactured.

the output tax change and the pre-GST input tax effects, considering the share of material costs and the elimination of tax cascading under the GST system.

To construct these key variables, one challenge is the variation in product classification systems. Specifically: the ASI uses NPCMS codes, VAT is recorded under ASICC codes, and both GST and central excise duty utilize HS codes. In terms of concordance between NPCMS and ASICC, we use concordance table from India's Ministry of Statistics and Programme Implementation (MOSPI).²⁰ For concordance between NPCMS

²⁰https://mospi.gov.in/sites/default/files/main_menu/national_product_classification/Concordance_of_ASICC_with_NPCMS_18apr12.pdf

Table OA.3 An Example of Variable Construction: Effective Tax Change Rate

Output tax change rate (τ_i^O):						
All pre-GST output items	Gross sales (sum of year 14/15-16/17)	Pre-tax (central excise duty + VAT)	Post-tax (GST)	Weighted pre-tax	Weighted post-tax	Weighted tax change rate
Item1	100	0.21	0.18	0.07	0.06	-0.01
Item2	200	0.13	0.12	0.087	0.08	-0.007
Sum	300			0.157	0.14	-0.017
Pre-GST input tax rate ($\tau_i^{I, Pre}$):						
All pre-GST input items	Purchase value (sum of year 14/15-16/17)	Pre-tax (central excise duty + VAT)	Weighted tax rate			
Item3	80	0.14	0.056			
Item4	120	0.06	0.036			
Sum	200		0.092			
Effective tax change rate (τ_i^E):						
Share of material cost	Pre-GST cascading factor	Post-GST cascading factor	Effective tax change rate			
0.7	0.35	0	-0.039			

and HS, since NPCMS is developed based on Central Product Classification (CPC) by extending one/two more digits of CPC, we use concordance table between CPC and HS from the United Nations Statistics Division (UNSD).²¹ When an NPCMS code maps to multiple possible tax rates, we compute a weighted average tax rate using similarity scores derived from the LLaMA large language model, which assesses textual alignment between product descriptions. These similarity scores serve as weights in computing the average applicable tax rate for each product.

Model Free Evidence Figure OA.3 shows how the composition of plants' output portfolios changed after the GST reform. Each panel corresponds to one GST rate bracket (0–5%, 5–12%, 12–18%, and above 18%) and each plant represents a point. The x-axis plots the share of a plant's total output in that tax bracket before GST, and the y-axis plots the corresponding share after GST. If plants had not adjusted their output mix, points would cluster along the 45-degree line. Instead, in all panels, points are widely dispersed away from this line, which indicates substantial changes in output composition after the reform. The direction and magnitude of these changes vary across plants: some increase the share of output in the bracket, others reduce it.

The distribution of points along the axes highlights both persistence and extreme shifts. Points at ((0,0)) or ((1,1)) correspond to plants that either never produced in that bracket or remained fully specialized in it, before and after the reform. By contrast, points near ((0,1)) or ((1,0)) reflect large changes, where plants enter or exit the bracket and move between no production and full specialization.

OA.4. Validation of Assumptions in Empirical Strategy

Anticipation Effect To test whether plants subjected to different effective tax changes show variations in outcome adjustments before the GST reform, we estimate the following equation:

$$\Delta y_{it} = \beta_0 + \beta_1 \tau_i^E + \phi' \Delta X_{it} + \gamma_t + \epsilon_{it}. \quad (\text{OA.1})$$

²¹<https://unstats.un.org/unsd/classifications/Econ>

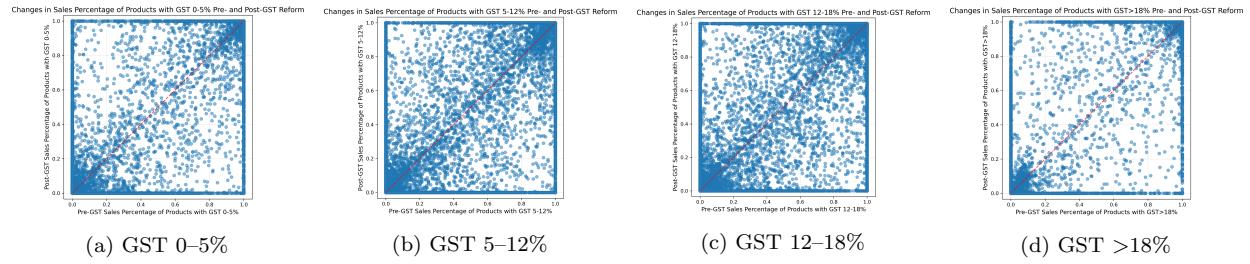


Figure OA.3 Share of plant sales in GST rate brackets before and after the GST reform. Each point is a plant; the x-axis shows the pre-GST sales share in the bracket and the y-axis shows the post-GST sales share.

Table OA.4 Impact of Effective Tax Changes on Outcome Changes

Variables	(1) D.Total Number of Outputs	(2) D.Number of Outputs with GST≤5%	(3) D.Number of Outputs with GST >18%	(4) D.GST Rate of Output Portfolio
Effective Tax Change	-0.049 (0.048)	-0.008 (0.028)	0.010 (0.011)	-0.000 (0.002)
D.Controls	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Observations	55,738	55,738	55,738	55,734
R-squared	0.002	0.001	0.000	0.000

Notes. This table presents the impact of effective tax change on delta variables of plants' output portfolio adjustments. The sample period is 2014/15-2016/17. The dataset for this table is organized at the plant-year-level. The control variables include changes of log total number of workers, log total asset, and share of exports in total gross sales. The standard errors are reported in parentheses. Standard errors are clustered at the plant level. The *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

where Δy_{it} denotes the change in outcome variables from time $t - 1$ to t , ΔX_{it} represents the change in control variables over the same period. The sample period is 2014/15 to 2016/17, prior to the GST reform. We also include year fixed effects. Appendix Table OA.4 shows no evidence of the anticipation effect, i.e., the effective tax changes did not impact outcome changes.

Common Support To test whether the distributions of covariates across treatment groups overlap, we divide plants into four groups based on the percentile of their effective tax change rates. Appendix Figure OA.4 plots the range from the 5th to the 95th percentile of two key covariates: total number of employees and total assets, across four effective tax change intervals. The significant overlap in these ranges suggests that the covariate values for each effective tax change interval are similar, supporting the common support assumption.

Exogenous Treatment To test whether the lagged outcome changes can predict subsequent treatment intensity changes, we estimate the following equation:

$$\tau_i^E = \beta_0 + \beta_1 D.Y_{it_0-1}^E + \phi' X_{it_0} + \epsilon_{it}. \quad (\text{OA.2})$$

where t_0 denotes the implementation year of GST reform, which is 2017/18. We use a cross-sectional sample in year t_0 since the treatment intensity τ_i^E is determined by the one-time GST rate change implemented in that year. Appendix Table OA.5 shows no evidence of the prediction effect, suggesting treatment exogeneity.

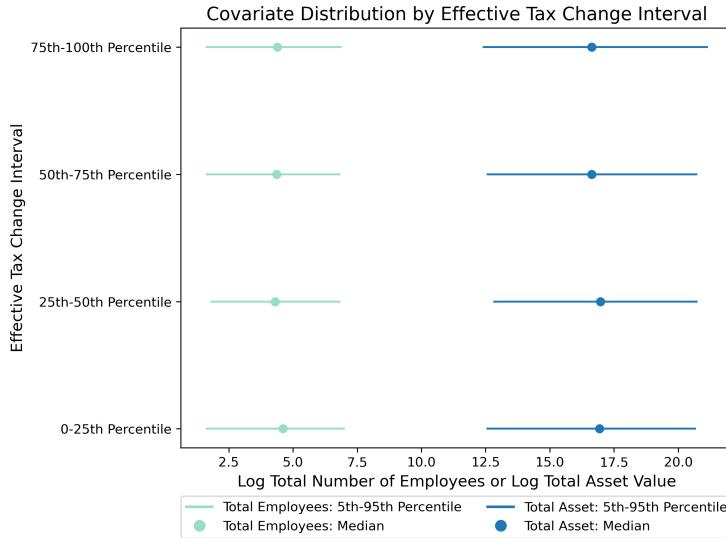


Figure OA.4 Common Support of Covariates Across Effective Tax Change Quantiles

Table OA.5 Impact of Pre-GST Outcome Changes on Effective Tax Change Rate

Variables	(1)	(2)	(3)	(4)	(5)
				Effective Tax Change Rate	
Lag D.Total Number of Outputs	0.000 (0.000)				-0.000 (0.000)
Lag D.Number of Outputs with GST≤5%		0.001 (0.001)			0.002 (0.001)
Lag D.Number of Outputs with GST >18%			0.002 (0.002)		0.002 (0.002)
Lag D.GST Rate of Output Portfolio				0.002 (0.028)	0.006 (0.029)
Controls	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Observations	24,560	24,560	24,560	24,560	24,560
R-squared	0.000	0.000	0.000	0.000	0.000

Notes. This table presents the impact of pre-GST outcome changes on effective tax change rate. The sample period is 2017/18. The dataset for this table is organized at the plant-year-level. The control variables include log total number of workers, log total asset, and share of exports in total gross sales in their differenced form. The standard errors are reported in parentheses. Standard errors are clustered at the firm level. The *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

OA.5. Additional Analyses of Output Portfolio Shifts

An Example of Constructing Sales-Weighted Average GST Rate of the Output Portfolio: In section 6.2, we develop a plant-year measure of the sales-weighted average GST rate of the output portfolio. Table OA.6 illustrates an example of how to construct this variable for one plant over two years, covering pre- and post-GST periods. Suppose the plant increases sales of the low-tax product (Item 1) and reduces sales of the high-tax product (Item 2) post GST reform. In that case, our measure of the sales-weighted average GST rate will decrease, indicating the plant's incentive to lower the output tax burden.

Impact on Sales of Products: We examine the impact on gross sales of products by GST bracket. Appendix Table OA.7 shows the results. Columns (1)-(4) reveal that plants exposed to higher effective tax change rates increase the gross sales value of low-GST-rate products, while reducing sales of high-GST-rate

Table OA.6 An Example of Variable Construction: Sales-Weighted Average GST Rate of the Output Portfolio

Output items	Gross sales	GST rate
2015/16 (pre-GST)		
Item 1	100	0.05
Item 2	200	0.18
Sales-weighted average GST rate		0.14
2018/19 (post-GST)		
Item 1	200	0.05
Item 2	100	0.18
Sales-weighted average GST rate		0.09

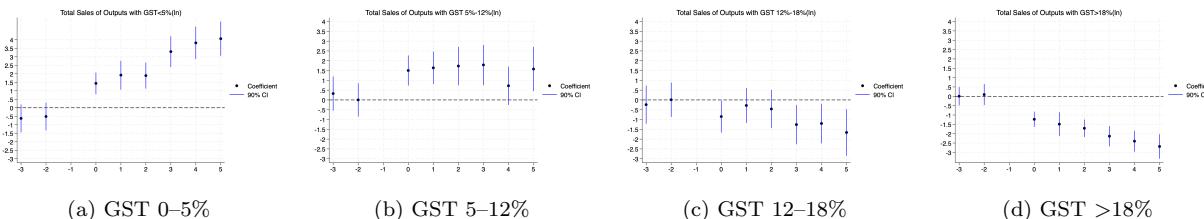
products. This suggests that a higher tax burden drives these plants to shift toward selling low-tax-rate products to mitigate the cost brought by increased taxes. The results are consistent with those in Section 6.1.

Table OA.7 Impact of GST Reform on Gross Sales of Outputs with Varying GST Rates

Variables	(1) Sales of Outputs with GST≤5%(ln)	(2) Sales of Outputs with GST in (5%,12%](ln)	(3) Sales of Outputs with GST in (12%,18%](ln)	(4) Sales of Outputs with GST >18%(ln)
Effective Tax Change × Post	2.919*** (0.347)	1.430*** (0.357)	-0.815** (0.366)	-1.900*** (0.232)
Controls	✓	✓	✓	✓
Plant FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Observations	277,164	277,164	277,164	277,164
R-squared	0.924	0.868	0.894	0.879

Notes. This table presents the impact of GST reform on plants' output portfolio. The sample period is 2014/15-2022/23. The dataset for this table is organized at the plant-year-level. The control variables include log total number of workers, log total asset, and share of exports in total gross sales. The standard errors are reported in parentheses. Standard errors are clustered at the plant level. The *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Parallel Trends and Long-term Effects: Appendix Figure OA.5, Panels (a) to (d) plot the event study coefficients for the gross sales across products with varying GST rates. Similarly to the main analysis, we find no significant differences between plants prior to the GST reform, supporting the parallel trends assumption. Moreover, the GST reform has long-term impacts on output portfolios rather than merely inducing temporary adjustments.

**Figure OA.5 Event Study Estimates for the Gross Sales of Products with Varying GST Rates**

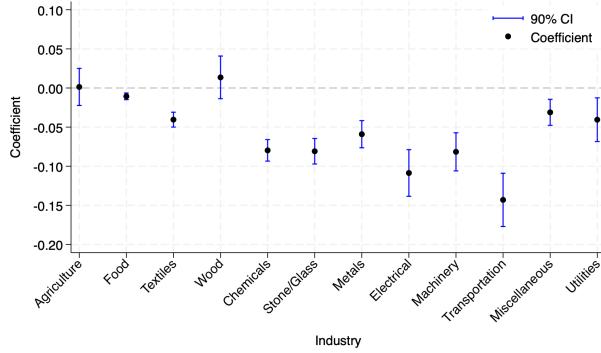


Figure OA.6 Impact of GST Reform on Sales-Weighted Average GST Rate for Multiple Industries

Industry Heterogeneity on GST Rate of Output Portfolio: The analysis in Section 6.2 reveals that plants adjust their output portfolio across different GST rate categories following the GST reform to reduce their sales-weighted average GST rate. These changes in sales-weighted average GST rate exhibit substantial heterogeneity across sectors, as industries differ in their product differentiation opportunities and supply chain flexibility, which shape their responses to the reform. To investigate this heterogeneity, we conduct a cross-sectional analysis by industry. Figure OA.6 plots the coefficients of β_1 in Equation (4) when y_{it} denotes the GST.

The equipment and machinery manufacturing sectors (transportation equipment, electrical products, machinery) have the strongest portfolio responses. From the supply side, these industries have greater product differentiation flexibility and more complex tax and supply chain structures, which create stronger incentives to optimize tax exposure. From the demand side, they face more competitive market environments that incentivize tax optimization.

In contrast, primary sectors such as agriculture and wood products show minimal adjustments, likely due to limited product differentiation, limited production flexibility, existing preferential tax treatment, and relatively inelastic demand. Consumer necessity industries (food, textiles) exhibit moderate portfolio shifts, balancing product differentiation opportunities with the constraints of producing essential goods with relatively inelastic demand.

OA.6. Example of the Product Similarity Measure and the Adjustment Costs of Reclassification and Reorganization

Example of the Product Similarity Measure: In Section 7, we constructed a product similarity measure based on cosine similarity between input portfolio vectors. We use a simple example to illustrate how this variable works. Let product k be raw milk of cattle and product j be cheese made from the milk of cattle. For each product $\ell \in \{k, j\}$, let

$$V_\ell = (w_{1\ell}, w_{2\ell}, \dots, w_{n\ell})$$

denote the vector of cost shares of input industries, where $w_{k\ell}$ is the share of input industry k in the total material cost of product ℓ , and n is the total number of input industries.

Suppose that for raw milk of cattle all material cost comes from the “raw milk of cattle” input industry, so

$$V_k = (0, 0, \dots, 1, 0, \dots, 0),$$

where the coordinate equal to 1 corresponds to the “raw milk of cattle” input industry and all other coordinates are zero. For cheese, assume that 97 percent of material cost comes from “raw milk of cattle” and 3 percent from “milk and cream,” so

$$V_j = (0, 0, \dots, 0.97, 0.03, 0, \dots, 0).$$

The cosine similarity between the two products is then

$$\cos(V_k, V_j) = \frac{V_k \cdot V_j}{\|V_k\| \|V_j\|} \approx 0.9995,$$

which is close to 1 and indicates that raw milk and cheese are produced with very similar input portfolios.

Adjustment Costs of Reclassification and Reorganization: We study the association between applying different adjustment options and changes in plant and machinery stock and in the ratio of gross sales over material costs after the GST reform. The empirical specification is as follows:

$$y_{it} = \beta_0 + \beta_1 \text{Adjustment}_i \times \text{Post}_t + \phi' X_{it} + \lambda_i + \gamma_t + \epsilon_{it}. \quad (\text{OA.3})$$

where Adjustment_i is a categorical variable denoting three options after the GST reform: introducing no new output, using a more reclassification strategy for new outputs (more than 50% of new outputs are reclassified), using a more reorganization strategy for new outputs (more than 50% of new outputs are reorganized). The option of no new output serves as the control group.

Table OA.8 Impact of Adjustment Options on Capital Stock and the Ratio of Gross Sales to Material Costs

Variables	(1) ln(Plant and Machinery) (0.7)	(2) ln(Plant and Machinery) (0.8)	(3) ln(Plant and Machinery) (0.9)	(4) ln(Gross Sales/Material Costs) (0.7)	(5) ln(Gross Sales/Material Costs) (0.8)	(6) ln(Gross Sales/Material Costs) (0.9)
Reclass × Post	0.048* (0.027)	0.047 (0.031)	-0.027 (0.038)	0.004 (0.005)	0.005 (0.005)	0.001 (0.007)
Reorg × Post	0.068*** (0.020)	0.060*** (0.019)	0.079*** (0.019)	-0.013*** (0.004)	-0.012*** (0.004)	-0.009** (0.004)
Controls	✓	✓	✓	✓	✓	✓
Plant FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	281,813	281,813	281,813	274,860	274,860	274,860
R-squared	0.904	0.904	0.904	0.724	0.724	0.724

Notes. This table presents the impact of GST reform on plants' capital stock and the ratio of gross sales over material costs. The sample period is 2014/15-2022/23. The dataset for this table is organized at the plant-year-level. The standard errors are reported in parentheses. Standard errors are clustered at the plant level. The *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table OA.8 shows that compared to the option of introducing no new output, plants with more reclassified new outputs show no significant differences in changes of capital stock of plant and machinery, as well as the ratio of gross sales to material costs. In contrast, plants with more reorganized new outputs are significantly correlated with increases in plant and machinery capital stock after the GST reform, and the ratio of gross sales to material costs decreases, indicating greater adjustment costs associated with the reorganization strategy.

OA.7. Production Function Parameter Estimates

In Section 8, we estimated industry-year-level production function parameters for materials, labor, and capital. Figure OA.7 plots the trends of average material, labor, and capital parameters over years, indicating that the estimates are stable over time.

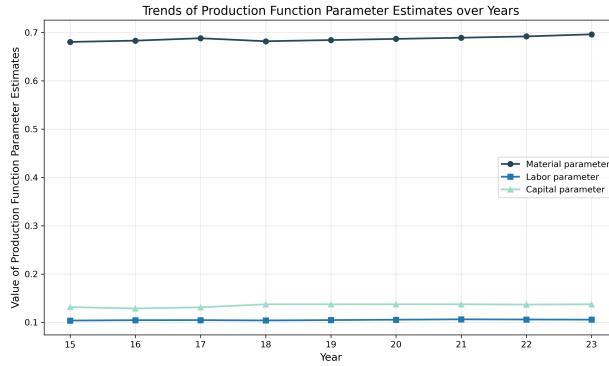


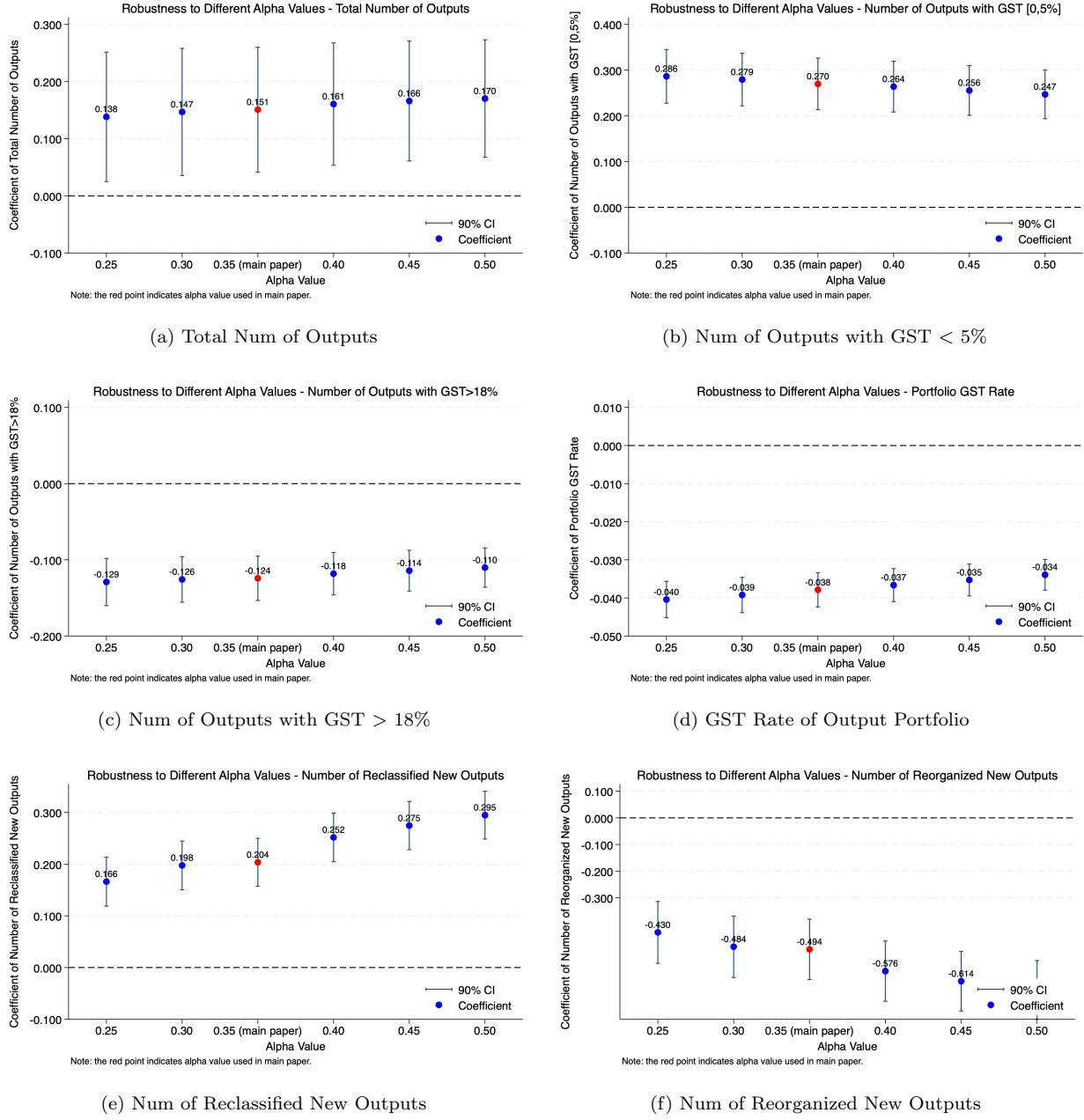
Figure OA.7 Trends of Production Function Parameter Estimates over Years

OA.8. Robustness Checks

In this section we assess the robustness of our main results to alternative implementation choices. In these robustness analyses, we (i) vary the cascading factor used to construct our treatment variable, (ii) replace the continuous effective tax change with discrete treatment groups, (iii) conduct placebo exercises, and (iv) confirm the operational productivity findings using a non parametric DEA measure of efficiency.

1. Robustness to α . We test the sensitivity of our results to alternative values of α , the cascading factor used in the construction of the effective tax change rate τ . In the main analysis, we set $\alpha = 0.35$ based on Ahmad and Poddar (2009). We find that our results remain robust for $\alpha = 0.25, 0.3, 0.4, 0.45$, and 0.5 . Appendix Figure OA.8 shows the results, where the red point indicates the α value used in the main analysis. The results still hold using different α values.

2. Discrete Effective Tax Change Rates. We replace our baseline specification, which uses a continuous effective tax change rate (τ^E) for plants' exposure to GST reform, with a discrete treatment measure that categorizes plants into three groups based on their effective tax change rate. Specifically, we define control group as plants with $\tau^E \in [-5\%, 0]$, negative treatment group as those with $\tau^E < -5\%$, and positive treatment group as $\tau^E > 0$. The results are reported in the Appendix Table OA.9. Column (1) shows that plants in the positive treatment group increase their total number of outputs, while those in the negative treatment group decrease their total number of outputs, consistent with the results that plants with higher effective tax change rates increase the total number of outputs (column (1) in Table 3). Similarly, columns (2)-(4) support the findings that plants with effective tax increases shift towards low-tax outputs (columns (2), (5) and (6) in Table 3), and columns (5)-(6) align with the results that plants with effective tax increases introduce more reclassified new outputs (Table 5).

**Figure OA.8 Robustness to Different α Values**

3. Placebo Tests. We conduct placebo tests to assess whether our baseline effects could arise spuriously from sampling variation or functional form. To do so, we randomly reshuffle the effective tax change rates across plants, holding each plant's outcomes and covariates fixed, and re-estimate Equation (4) on each placebo sample. Appendix Figure OA.9 plots the distribution of the placebo coefficients based on 500 such iterations and marks the baseline estimate. All the coefficients lie well outside the central part of the placebo distribution, falling beyond the 95th percentile or below the 5th percentile. We also show the true baseline coefficients, which are all far from the placebo distribution. This pattern indicates that the main effects we estimate are unlikely to be driven by chance.

Table OA.9 Robustness Analyses of Output Portfolio Adjustments Using Discrete Treatment Measure

Variables	(1) Total Number of Outputs	(2) Number of Outputs with GST≤5%	(3) Number of Outputs with GST >18%	(4) GST Rate of Output Portfolio	(5) Number of Re-Classified New Outputs (0.8)	(6) Number of Re-Organized New Outputs (0.8)
Negative treatment	-0.036*** (0.013)	-0.017*** (0.005)	0.009*** (0.003)	0.004*** (0.000)	-0.016*** (0.005)	0.016*** (0.005)
Positive treatment	0.068*** (0.016)	0.039*** (0.008)	-0.022*** (0.005)	-0.003*** (0.000)	0.049*** (0.008)	-0.049*** (0.008)
Controls	✓	✓	✓	✓	✓	✓
Plant FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	277,164	277,164	277,164	277,151	277,164	277,164
R-squared	0.782	0.914	0.853	0.948	0.647	0.935

Notes. This table presents the impact of GST reform on plants' output portfolio adjustments using discrete treatment measure. The sample period is 2014/15-2022/23. The dataset for this table is organized at the plant-year-level. The control variables include log total number of workers, log total asset, and share of exports in total gross sales. The standard errors are reported in parentheses. Standard errors are clustered at the plant level. The *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

4. Measuring operational efficiency via Data Envelopment Analysis (DEA). As a robustness check on our TFP-based results, we construct an alternative operational efficiency measure using the Data Envelopment Analysis (DEA). DEA is a linear programming technique that constructs a non-parametric frontier over the data, determining an optimal set of weights for each input and allowing firms to reach the production efficiency frontier through diverse strategies. Following Section 8, we select three key inputs: fixed capital, labor cost, material cost, and use gross sales value as the output.

For our DEA-based measure, we use ASI data items on fixed capital (including building, plant and machinery, transport equipment, computer equipment, pollution control equipment), total employee wages, purchased value of domestic and imported materials, and energy consumption value (including electricity, petrol, coal and gas). We calculate the DEA scores for the sample factories within each two-digit NIC industry annually. We adopt a VRS (Variable Returns to Scale), input-oriented DEA model, following Banker et al. (1984). The VRS model enhances the original Charnes et al. (1978) framework by incorporating a convexity constraint that accounts for non-proportional changes in output relative to input. The dual form of the linear programming problem under the Banker, Charnes, and Cooper (BCC) model is formulated as follows:

$$\begin{aligned} & \min \theta \\ \text{s.t. } & \sum_i x_{ij} \lambda_i \leq \theta x_{jp} \quad \forall j \\ & \sum_i y_{ik} \lambda_i \geq y_{kp} \quad \forall k \\ & \sum_i \lambda_i = 1 \\ & \lambda_i \geq 0 \quad \forall i \end{aligned}$$

where θ is the efficiency score for decision making unit (DMU) p . x_{ij} represents the amount of j -th input for DMU i . y_{ik} represents the amount of k -th output produced by DMU i . λ_i denotes the intensity variables (weights) for constructing the efficiency frontier. DEA is an input-oriented approach that minimizes inputs given the DMU's outputs.

Appendix Table OA.10 shows that plants experiencing tax increases suffer from more efficiency losses, as indicated by the negative coefficient of $EffectiveTaxChange \times Post$ in Column (1), which is consistent with the results in Section 8.

Table OA.10 Impact of GST Reform on Production Efficiency Measured by DEA Method

Variables	(1)
	Production Efficiency (DEA)
Effective Tax Change \times Post	-0.155*** (0.016)
Controls, Plant FE, Year FE	✓
Observations	274,857
R-squared	0.685

Notes. This table presents the impact of GST reform on plants' production efficiency. The sample period is 2014/15–2022/23. The dataset for this table is organized at the plant-year-level. The control variables include log total number of workers, log total asset, and share of exports in total gross sales. The standard errors are reported in parentheses. Standard errors are clustered at the firm level. The *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

OA.9 A Simple Model of Cost Shocks and Reorganization

This section develops a simple model of cost shocks and production reorganization. A tax reform changes the relative tax burden on different product categories and thus generates heterogeneous cost shocks across plants. In response, a plant can (i) absorb the shock, (ii) reclassify its product into a lower tax slab product through minor modifications that may reduce efficiency, or (iii) reorganize production more deeply by adopting a new technology or product line that alters both tax treatment and input requirements, at the cost of a larger investment. Our model delivers a cost–efficiency trade-off and explains how plant size and the size of the tax shock shape the choice between these adjustment margins. We then provide an extension that links these decisions to working capital and inventory productivity.

Environment and Tax Structure

Consider a plant that produces a single final good and sells it at an exogenous price p . To produce one unit of output, it uses a composite input whose pre tax unit cost is normalized to 1. The tax system has two slabs: (i) a high rate slab with tax rate τ_H , and (ii) a low rate slab with tax rate $\tau_L < \tau_H$. The tax reform increases the tax rate on the plant's original product so that it now falls into the high slab. A related product variant remains available in the low slab. The relevant tax gap is

$$\Delta\tau \equiv \tau_H - \tau_L > 0.$$

Before the reform, the plant produces the original product with a baseline technology and faces the high slab only after the reform. After the reform, the plant chooses one of three options: (i) **No change** (N): keep the original product and technology in the high slab; (ii) **Reclassification** (R): implement minor changes to the product or process that allow the output to be classified in the low slab, at the cost of potentially lower production efficiency through higher per unit input requirements; or (iii) **Reorganization** (O): undertake a deeper change in technology or product line in the low slab that can deliver a different pattern of tax treatment and input use, but requires a larger fixed investment and may involve larger short-run efficiency losses. Let q denote the plant's output scale (or capacity). Fixed costs are spread over q and hence matter more for small plants.

Technologies, Unit Costs, and Efficiency

We normalize the pre reform technology as follows. Under the original technology, one unit of output uses one unit of the composite input. The non-tax unit cost is 1, so the tax inclusive unit cost if the plant stays in the high slab is

$$C_N = (1 + \tau_H). \quad (\text{OA.4})$$

We interpret efficiency as the inverse of non-tax input per unit of output. Higher input requirements imply lower efficiency and lower material productivity.

Reclassification. Under reclassification, the plant keeps the underlying technology but modifies the product or process just enough to qualify for the low slab. Examples include altering the mix of ingredients, changing pack sizes, or running a separate finishing step so that the product falls under a different GST code. The pre reform recipe is assumed to be cost minimizing for the given product and quality level. Deviations that are driven by classification rules rather than production considerations can raise per unit resource use. For instance, smaller batch sizes, extra handling, or non functional ingredients chosen to meet classification thresholds may require additional labor time and materials. We capture this possibility by assuming that reclassification increases the amount of non-tax input needed per unit of output by a fraction $\delta_R > 0$, so that non-tax input per unit becomes $1 + \delta_R$. The reclassified product is taxed at the low rate τ_L . Reclassification also requires a fixed adjustment cost $F_R > 0$ (engineering work, legal advice, and documentation), which translates into a per unit cost of F_R/q . The tax inclusive unit cost under reclassification is therefore

$$C_R = (1 + \tau_L)(1 + \delta_R) + \frac{F_R}{q}. \quad (\text{OA.5})$$

Reorganization. Under reorganization, the plant undertakes a deeper change in technology or product mix. In many settings, such changes aim to reposition the product in the tax schedule and adapt input use to the new environment, but they can also be more disruptive for production. We capture this possibility by assuming that reorganization increases the amount of non-tax input needed per unit of output by a fraction $\delta_O > 0$, so that non-tax input per unit becomes $1 + \delta_O$. It is natural to think that deeper changes can involve larger short-run efficiency losses, so in many applications one may have $\delta_O \geq \delta_R$, although this inequality is not required for the algebra below. The reorganized product is taxed at the low rate τ_L . Reorganization requires a fixed investment $F_O > F_R$, which translates into a per unit cost of F_O/q . The tax inclusive unit cost under reorganization is

$$C_O = (1 + \tau_L)(1 + \delta_O) + \frac{F_O}{q}. \quad (\text{OA.6})$$

Profits and the Firm's Problem. We focus on per unit profits and treat output price p as common across technologies. Under option $k \in \{N, R, O\}$, per unit profit is

$$\pi_k = p - C_k,$$

so the plant chooses the option with the lowest unit cost:

$$k^* \in \arg \min_{k \in \{N, R, O\}} C_k. \quad (\text{OA.7})$$

²²This abstraction holds demand and output prices fixed across technologies and focuses attention on how tax induced cost shocks interact with efficiency, adjustment costs, and scale.

The Cost–efficiency Trade-off

Reclassification is attractive only if the tax savings it delivers are large enough to compensate for the efficiency loss and the fixed adjustment cost. Specifically, reclassification is preferred to no change if $C_R < C_N$, that is

$$(1 + \tau_L)(1 + \delta_R) + \frac{F_R}{q} < 1 + \tau_H. \quad (\text{OA.8})$$

Rearranging,

$$\begin{aligned} 1 + \tau_H - (1 + \tau_L)(1 + \delta_R) &> \frac{F_R}{q} \\ \Rightarrow (\tau_H - \tau_L) - \delta_R(1 + \tau_L) &> \frac{F_R}{q}. \end{aligned} \quad (\text{OA.9})$$

Using $\Delta\tau \equiv \tau_H - \tau_L$, the firm chooses reclassification if

$$\Delta\tau > \delta_R(1 + \tau_L) + \frac{F_R}{q}. \quad (\text{OA.10})$$

On the left hand side is the per unit tax saving from moving to the low slab. On the right hand side is the sum of the per unit efficiency loss, $\delta_R(1 + \tau_L)$, and the fixed adjustment cost per unit, F_R/q . Condition (OA.10) captures a clear cost–efficiency trade-off: (i) larger tax shocks $\Delta\tau$ make reclassification more attractive, (ii) larger plants (higher q) can spread F_R over more units, so they reclassify at smaller tax shocks, and (iii) if reclassification is very disruptive for efficiency (large δ_R), the required tax shock to justify it is larger. For small tax shocks, inequality (OA.10) fails and the plant keeps the original product and technology, absorbs the tax change, and retains baseline efficiency. Section 11.4 extends this comparison to the choice between reclassification and reorganization.

Reclassification versus Reorganization

Given that the plant may wish to escape the high slab, a natural question is whether it prefers low cost reclassification or deeper reorganization. The firm prefers reorganization to reclassification if $C_O < C_R$. Using the expressions in (OA.5) and (OA.6), this condition is

$$(1 + \tau_L)(1 + \delta_O) + \frac{F_O}{q} < (1 + \tau_L)(1 + \delta_R) + \frac{F_R}{q}. \quad (\text{OA.11})$$

Rearranging,

$$\begin{aligned} (1 + \tau_L)[(1 + \delta_O) - (1 + \delta_R)] &< \frac{F_R - F_O}{q} \\ (1 + \tau_L)(\delta_O - \delta_R) &< \frac{F_R - F_O}{q}. \end{aligned} \quad (\text{OA.12})$$

Let $\Delta F \equiv F_O - F_R > 0$. Multiplying both sides of (OA.12) by -1 reverses the inequality and yields

$$(1 + \tau_L)(\delta_R - \delta_O) > \frac{\Delta F}{q}. \quad (\text{OA.13})$$

Equation (OA.13) highlights how the relative efficiency of the two technologies and the fixed cost difference shape the choice between reclassification and reorganization.

- If $\delta_O \geq \delta_R$ and $F_O > F_R$, then the left hand side of (OA.13) is non positive while the right hand side is positive, so the inequality cannot hold. In this case, reorganization is never preferred in this simple unit cost comparison, and among plants that move to the low slab, reclassification is the dominant adjustment margin.

- If $\delta_O < \delta_R$, reorganization uses fewer non-tax inputs per unit of output than reclassification in the long run. The left hand side of (OA.13) is then positive, and there exists a size threshold $q^* > 0$ such that reorganization is optimal for sufficiently large plants. Solving (OA.13) for q gives

$$q > q^* \equiv \frac{\Delta F}{(1 + \tau_L)(\delta_R - \delta_O)}. \quad (\text{OA.14})$$

In the second case, the extra fixed cost of reorganization is only worthwhile for plants with scale q above q^* . For $q < q^*$, the plant chooses the low fixed cost reclassification technology, which reduces its tax rate but comes with a larger efficiency loss than reorganization. For $q > q^*$, the plant finds it optimal to invest in the high fixed cost reorganized technology, which both lowers the tax rate and yields a more efficient steady state input use than reclassification. Combining (OA.10) and (OA.14), the firm's choice can be summarized as:

- **No change (N):** if the tax shock $\Delta\tau$ is small and (OA.10) does not hold, the plant stays in the high slab and keeps its original technology.
- **Reclassification (R):** if (OA.10) holds but $q \leq q^*$, the plant moves into the low slab via minor recipe changes and accepts the associated efficiency loss.
- **Reorganization (O):** if (OA.10) holds and $q > q^*$, the plant undertakes deeper reorganization, pays the larger fixed cost, and adopts the technology that delivers the lower steady state unit cost among the two low slab options.

Figure OA.10 illustrates these regions in the $(q, \Delta\tau)$ space for parameter values that satisfy $\delta_O < \delta_R$ and $F_O > F_R$, so that q^* in (OA.14) is well defined. Larger tax shocks and larger plant size tilt the plant from no change to reclassification and then to reorganization.

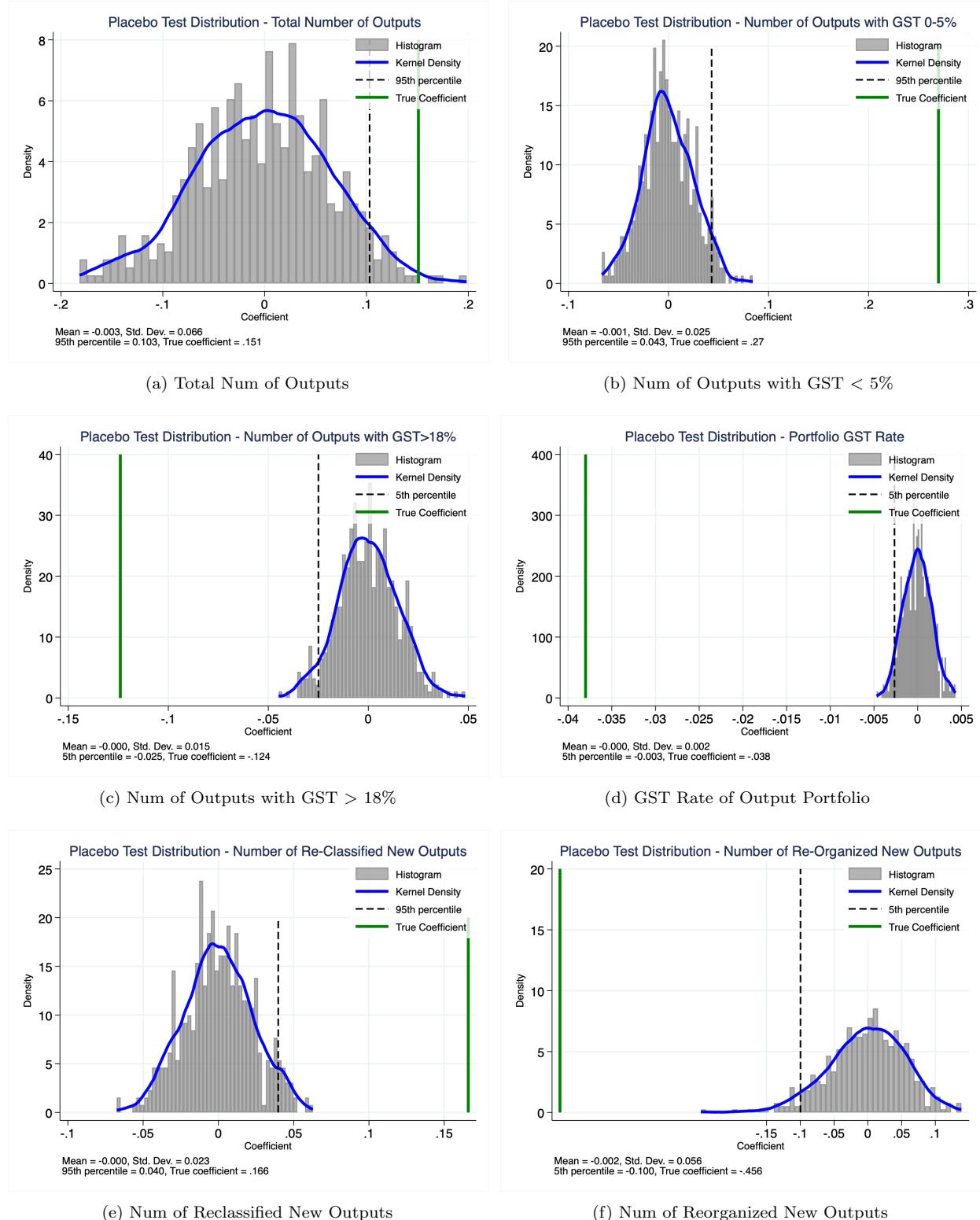


Figure OA.9 Placebo Tests: Histogram and Density Plot of Placebo Estimates of GST Effect on Plants' Outcomes, Based on 500 Iterations

Note. Histogram and kernel density plot of TWFE OLS coefficients of effect of GST reform on plants' production decisions from estimating Equation (4), with randomly reshuffled effective tax change rates across plants (500 Iterations).

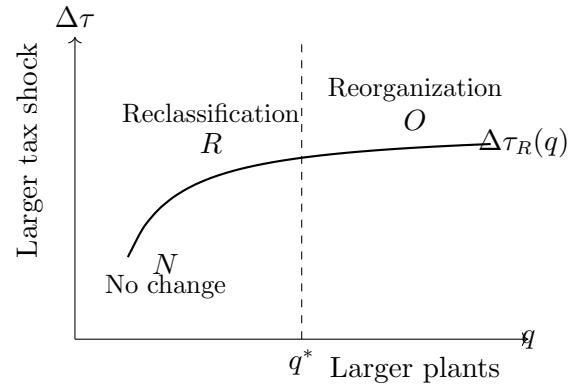


Figure OA.10 Choice of strategy as a function of plant size q and tax gap $\Delta\tau$. For small shocks the plant keeps its original technology. For intermediate shocks and small plants, reclassification is optimal. For large plants and sufficiently large shocks, reorganization dominates.