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The rise of superstar firms in the United States: The role of global sourcing

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ABSTRACT

Recent trends of global sourcing, market concentration, and aggregate markup have garnered increased attention. This paper examines the impact of global sourcing of inputs on market structure and markup changes in the United States. We develop a theoretical model with heterogeneous firms that suggests only the most-productivity firms will self-select to source inputs overseas, resulting in an increase in the markups and market shares of these leading firms, while lower-productivity firms are crowded out. Based on the theoretical analysis, aggregate markup rises due to both the within-firm markup adjustments and market share concentration among leading firms. We then provide empirical evidence supporting our theoretical predictions, analyzing the effect of imported inputs on markup adjustments, market shares, and industrial markups in the United States over the past four decades. Our results highlight the importance of firms' self-selection effect in the global sourcing market and its impact on market outcomes. Failing to account for this influencing channel could lead to an underestimation of the contribution of input globalization to the rise of markup and other market consequences.

1. Introduction

The rise of market power and its macroeconomic impacts have been widely discussed in recent economic literature (Azar et al., 2020; Barkai, 2020; Ganapati, 2021; Gutierrez and Philippon, 2016; Kwoka et al., 2015; Traina, 2018). In particular, the increase in average markups since the late 1970s and the concentration of market share among leading firms (i.e., the most-productivity firms) have been identified as factors contributing to the decline of labor share in the United States (Autor et al., 2020; De Loecker et al., 2020; Covarubias et al., 2020). At the same time, globalization in the last decades has transformed how and where firms source their inputs, and the process of globalization has intensified foreign competition, which may eliminate distortions associated with monopoly power. However, literature on trade has largely concentrated on exporting rather than importing, and the impact of imported input penetration on market concentration remains unclear and requires further study.

This paper investigates the relationship between input globalization, market structure, and the rise of aggregate markup in the United States. Our study aims to address two critical questions surrounding the increasing markup in the country. First, we examine whether input globalization, either partially or entirely, explains the emergence of superstar firms and the associated increase in

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markup. Second, we explore the mechanism through which input globalization affects market structure and aggregate markup. Many studies have identified potential causes of the emergence of superstar firms, including adoption of new technologies (Südekum et al., 2020), changes in the business environment (Kroen et al., 2022; Gallemore and Maydew, 2023), and the rise of superstar exporters (Panon, 2022; Ciliberto and Jäkel, 2021). However, the specific link between global sourcing, imported input penetration, and the rise of superstar firms remains unclear. Our study therefore situates in the broader literature on the rise of superstar firms and increasing returns. Additionally, while input globalization can increase aggregate markup by bringing cost savings and reallocating resources to leading firms, it may also deter markup by increasing competition in upstream markets, creating an uncertain net effect. Our research objective is to examine whether the depth of the outsourcing process contributes to the rise of leading firms and the associated increase in aggregate markup in the United States. We seek to provide insights into the efficiency of resource allocation in each industry and the potential impact of input globalization on market power. We calculate the aggregate markup as an indicator of resource allocation efficiency in each industry, as described by De Loecker et al. (2020), and analyze changes in market concentration and profitability following input trade liberalization. Through our analysis, we aim to shed light on the role of superstar firms in shaping market structures and aggregate markets. Our study contributes to the wider literature on the emergence of superstar firms and increasing returns by connecting the paper's core mechanism to this broader literature. By examining the relationship between input globalization, market structure, and aggregate markup, we aim to provide a more comprehensive understanding of the efficiency of resource allocation and market power in the United States.

To address these research questions, we propose a theoretical framework that links the change in industrial aggregate markup to the changes in the markups and market shares among heterogeneous firms, accounting for firms' self-selection in the global sourcing market. An increase in aggregate markup is generally due to three key changes caused by the liberalization of input trade: Rise of markups and market shares of the importing firms (high-productivity firms) with accessing to the cheaper imported inputs; more firms begin to import and use foreign inputs; and low-productivity firms are crowded out of the market. We then empirically examine the relationship between change in the average markup and the penetration of imported inputs in the process of globalization over the past forty years. Using U.S. firm-level micro panel data and input-output tables, we present empirical evidence on the relationship between the increasing trend of imported input penetration and the rise of market power. Our analysis of the mechanism reveals a noteworthy outcome: firms experience a positive impact on their markups due to imported input penetration, which reflects within-firm adjustments. Meanwhile, market shares tend to concentrate on leading firms with high productivity and markups, indicating between-firms' adjustments. The combination of these adjustments contributes to the rise of industrial aggregate markup. Our study provides significant evidence of the connection between input-trade liberalization and market power, emphasizing the significance of comprehending the implications of globalization on market structure.

Our analysis proceeds in three steps. First, we develop a conventional theoretical model that links market structure to global sourcing. We extend Melitz and Ottaviano (2008) model to include the firm's input procurement decision and highlight the firm's choice on importing foreign input in the spirit of Amiti et al. (2014), wherein the markup changes with the extensive margin of sourcing decisions. As we include the firm's choice to import intermediate inputs in our model of quasi-quadratic preferences, our model generates linear equations that relate changes in markup to fluctuations in the penetration rate of foreign inputs. The capability to profit from importing foreign inputs depends on a firm's trade-off between the potential marginal cost advantage and the fixed cost incurred from using the imported inputs. Since it requires a fixed cost to select cost-efficient intermediate inputs and start importing, the capability to benefit from the reduction of trade costs and to employ imported inputs in production depends on the level of productivity. High-productivity firms that are affordable of the associated fixed costs and accessible to import inputs can expand their cost advantage over their less productivity competitors.¹ Our theoretical analysis provides a tractable framework to illuminate the effects of input trade liberalization on industrial structure and dynamics, e.g., firms' sourcing and operation decisions, resource-reallocation effect among heterogeneous firms, and growth trend of aggregate markup. We add to the existing theoretical discussion by incorporating these features of industrial evolution and reaching rich predictions that are reconciled with a bulk of empirical findings from the previous literature as well as this paper.

Second, we present descriptive statistics and stylized facts on the rise in import penetration and markups since the 1970s before we turn to the empirical analysis. We show that the ratio of imports to GDP increased from around 4.2% in 1960 to around 16.5% in 2014, while the average markup increased from around 1.2 to over 1.6 between the late 1970s and 2014. The impact of import penetration on markup is ambiguous. According to standard trade theory, less markup is predicted due to competition from imported goods. However, if the market is characterized by imperfect competition, a reduction in trade costs due to globalization will make heterogeneous effects on the markups of firms that import inputs and those that use domestic inputs only. In practice, we distinguish and measure the import penetration ratios of outputs and intermediate inputs separately, taking the fact that the output of one sector can be used as an input for another into account. When we look at the import of inputs, we find a strong correlation between the rise in the penetration ratio of imported inputs and the weighted average markup at the 2-digit level sector. However, the effect of the imported penetration of the final product on markup is ambiguous. This may be due to a combination of foreign products competing with domestic products as well as the cost savings that multinational enterprises experience when they offshore production and re-import the final product.

Third, our research investigates the relationship between the rise of market power by the U.S. firms, particularly the leading firms,

¹ Constrained by our data structure, we cannot directly check the relationship between U.S. firms' productivity and their importing performance. Alternatively, we empirically check this relationship with Chinese manufacturing firm data. The relevant result shows that the firms with higher TFP are more likely to import inputs from foreign markets.

and the rise of imported input penetration over the last four decades. We estimate the production function using the firm-level panel data, which contains key balance-sheet variables such as sales, cost of goods sold (COGS), employee number, capital, etc., retrieved from the WRDS-Compustat database. Relying on this dataset spanning from 1977 to 2014, we apply the production-based approach suggested by [De Loecker et al. \(2016\)](#) to estimate the U.S. firms' markups. We then calculate the level of direct import penetration ratio of the final products in each sector by analyzing US import and export data compiled from UN COMTRADE and USA Trade Online, wherein such direct import penetration is named as the horizontal import penetration (HIMP) in this paper. By combining the input-output benchmark tables at the 6-digit industry level from the Bureau of Economic Analysis (BEA), we measure the usage ratio of imported inputs of a specific sector by weighting the direct import penetration ratios of other sectors with the input-usage ratios of this sector from other sectors, wherein such measurement for the import penetration ratio of inputs is called the vertical import penetration (VIMP) in this paper. VIMP measures the ratio of the value of imported intermediate inputs to the total value of intermediate inputs used in production, which reveals the extent to which firms rely on imported intermediate inputs in their production process. Our empirical investigations use the industry-level VIMP to measure the level that firms' exposure to the input globalization, and reach the result that a 0.1 unit increase in VIMP leads to an average increase of around 3.4% in markup. Based on this empirical result, we approximate that the rise of imported input penetration contributes to around 17% of the markup increment from 1977 to 2014. We also investigate the mechanism of the causal relationship between the rise of global sourcing and growth trend of markups by the U.S. firms, focusing on the structural changes of the industry. Our analysis finds that as the VIMP increases, high-productivity firms expand their markups and sales more, while the lowest productivity firms reduce their market shares and surviving probability in the market, suggesting a concentration trend of market shares and market power among the leading firms.² Our results are reconciled with the findings by [Autor et al. \(2020\)](#) and [De Loecker et al. \(2020\)](#) on the consequences of the rising superstar firms. Our baseline estimation survives multiple concerns of the model, including alternative markup measures, alternative benchmark weighting in accounting for input penetration, and the use of a difference-in-difference approach taking into account the positive import shock as a consequence of the elimination of trade uncertainty with China as in [Pierce and Schott \(2016\)](#).

This paper contributes to the existing literature in both empirics and theory. First, our study is among the first waves to discuss the effect of imported input penetration on the industry's aggregate markup under a general equilibrium model. Our theoretical framework is closely related to [Melitz and Ottaviano \(2008\)](#), [Antràs et al. \(2017\)](#), [Halpern et al. \(2015\)](#), [Hornok and Muraközy \(2019\)](#), and [Bustos \(2011\)](#). [Melitz and Ottaviano \(2008\)](#) develop a monopolistic competition model with heterogeneous firms, which has been a workhorse model that predicts intra-industry reallocation between firms with variable markups following trade liberalization. [Antràs et al. \(2017\)](#) study the self-selection in using the foreign inputs by heterogeneous firms. They emphasize the role of fixed importing costs played in determining firms' sourcing decisions, and find a positive relation between the firm's productivity and the usage intensity of foreign inputs. Our theoretical model differs from [Antràs et al. \(2017\)](#) by allowing markup to be variable and linked with the usage of foreign inputs in the production process. [Halpern et al. \(2015\)](#) estimate the productivity gains from improved access to foreign inputs. By assuming a constant elasticity of substitution (CES) utility function, they propose a static model of industry equilibrium in which firms use both domestic and imported intermediate goods to produce products. In addition, the CES utility implies a constant markup, making it unsuitable to feature the markup changes regarding aggregate shocks. We instead employ the linear demand system as in [Melitz and Ottaviano \(2008\)](#) and trace in detail how imported input penetration plays a role in the cost structure and profitability of firms that have better ability to utilize sourcing opportunities.³ [Hornok and Muraközy \(2019\)](#) also employ a linear demand function to analyze the self-selection behavior in the outsourcing market by heterogeneous firms, and find a positive relation between firms' export/import status and markups. However, [Hornok and Muraközy \(2019\)](#) does not consider the effect of trade liberalization on resource reallocation under the general equilibrium.

Our theoretical analysis shares with [Bustos \(2011\)](#), which paper investigates the effect of trade liberalization on heterogeneous firms with regards to innovation promotion using the Argentinian data. Our theoretical framework differs from [Bustos \(2011\)](#) in research targets. We examine heterogeneous firms' self-selection feature in import status and the effects of trade liberalization on their profitability and market shares with various import statuses, while [Bustos \(2011\)](#) analyzes the effects of trade liberalization on firms' innovation investment decisions. [Bustos \(2011\)](#) predicts that firms will increase their innovation investments once they gain more market sales after trade liberalization, given that they can now afford of the high fixed innovation costs. Our model predicts that markup expansion can be driven by the reduction in the costs of imported inputs as well as the market expansion of leading firms. The major settings of our model are based on the literatures introduced above. Reduced global sourcing costs encourage a firm to start import or import more foreign inputs, which then increases its markup, but the firm's access to foreign inputs is subject to its ability to pay the fixed import costs. Our model indicates that the firm with higher productivity level is more likely to source inputs from the international market. A decrease in importing costs will reduce the production costs of the importing firms, which enhances the competition strengths and profitability of these firms. In turn, this implies that input-trade liberalization impacts existing market players in an asymmetric manner. Firms that are not importing, which are typically low productivity firms, are more likely to be squeezed out of the market by firms that are importing. As the markups and market shares of superstar firms rise and low productivity firms with relatively low markups leave, industry's aggregate markup will increase.

² The positive relation between firms' productivity and endogenous selection to import has been empirically confirmed by [Hornok and Muraközy \(2019\)](#), [Abreha \(2019\)](#) and [Elliott et al. \(2019\)](#).

³ [Fan et al. \(2018\)](#) and many other literatures have found that a reduction of variable cost leads to a higher markup, which indicates incompleteness of pass-through of the variable cost. Thus, it is not suitable to use the CES utility function, which leads to the completed pass-through of the change of variable cost.

Second, it adds to the vibrant empirical literature on the effects of trade liberalization on market power by providing evidence on the role of import penetration played in the rise of leading firms and markup evolution. Previous studies have shown a decrease trend of firms' markups with exposure to an increasing market competition intensity following the trade liberalization (Amiti and Konings, 2007; Bas and Strauss-Kahn, 2015; De Loecker et al., 2016; Lu and Yu, 2015). Import penetration lead to an increased market competition from foreign producers, which exerts pressure on firms to lower their markups (De Loecker et al., 2016; Edmond et al., 2015; Long and Miao, 2020; Liu and Ma, 2020). For example, Badinger (2007) finds a decline of markups in manufacturing sectors following the EU's Single Market Programme. Edmond et al. (2015) also find a reduction effect of trade liberalization on markup and markup dispersion using the manufacturing firm data from Taiwan (China). Epifani and Gancia (2011) document the stylized facts one the markup dispersion across industries over time with exposure to trade. In an oligopoly framework with a CES utility function, they demonstrate the substantial costs from markup heterogeneity across firms and the possibility of welfare losses from the asymmetric trade liberalization. Feenstra and Weinstein (2017) analyze the welfare gains of globalization based on symmetric translog preferences and assess the channels of variety-increase and markup-decline. Our study differs from these papers by showing that higher imported input penetration leads to higher sectoral aggregate markup, which is driven by the lower input costs and scale growth earned by the leading firms that participate in the global value chain and input globalization process. Our analysis nests the spillovers effect of import penetration when the final goods in some sectors can be used as inputs in other sectors, emphasizing the deterrence-effect of input globalization on resource-allocation efficiency.

On the effect of cost reduction in imported inputs, literatures have well documented a consistent positive effect of input-trade liberalization on firms' markups. Using Chinese firm-level data, Manova and Zhang (2012) document the fact that firms that are larger and charge higher prices will import more expensive inputs and provide multiple-quality products across destinations. Ludema and Yu (2016) explain the incomplete pass-through of tariff reductions by the upgrading of the product quality, which are estimated to be greater for higher productivity firms. Amiti et al. (2014) develop an oligopoly framework with variable markups and accessible to imported inputs by firms, and find that the firms with top import shares have relatively low exchange rate pass-through. Brandt et al. (2017) find that cuts in output tariffs reduce markups while cuts in input tariffs raise both markups and productivity of firms with the Chinese manufacturing firm data.⁴ Our study differs from the existing studies by exploring the macroeconomic trend of markup evolution, and structurally decomposing the rise of aggregate markup into the rise of markups within firms and resource-allocation toward the leading firms with exposure to input globalization.

Lastly, this paper contributes to the literature that investigates the global trend of rise of superstar and its consequences by exploring whether and to which extent the input globalization can be accounted as an induction factor. De Loecker and Eeckhout (2018) documents the increasing trend of global market power, which is more pronounced in the developed world than in emerging economies. Specifically, the average global markup increased from 1.2 to 1.6 between 1980 and 2014. In the United States, the average markup has been rising dramatically since the 1980s, and this trend is believed to be associated with many other macroeconomic trends, such as the decline in labor and capital share, the decrease in wages for low-skilled labor, and the slowdown in aggregate output (De Loecker et al., 2020). A related study is Elsby et al. (2013), which examines the impact of globalization and rising imports on the decline of labor share. Their analysis, which employs cross-industry regressions and graphs, shows that the change in import exposure accounts for 22% of the cross-industry variation in payroll-share changes.

This study is also closely to the works by Autor et al. (2020) and Hornok and Muraközy (2019). Autor et al. (2020) argue that the decline in aggregate labor share is driven by market concentration toward superstar firms, and shares a parallel growth trend with increased profits, decreased investment, and decreased wages. Our study differs from Autor et al. (2020) by focusing on the decomposition of growth trend of aggregate markup, rather than the labor share. Our study further attributes the market concentration (partially) to the input globalization process, which is not explored by Autor et al. (2020). Using Hungarian data, Hornok and Muraközy (2019) present evidence of a positive relationship between firms' importing status and markups, and further break down these positive relationships into the self-selection of high-markup firms in the outsourcing market, an increase in product quality, and a reduction in marginal production costs. Hornok and Muraközy (2019) identify firms' self-selection behavior in the outsourcing market to be the dominant factor in the positive relationship between firm export/import status and markups. Our study expands the works of Hornok and Muraközy (2019) by discussing the resource-allocation effect and the aggregate markup changes along with the industrial dynamics. Our aim is to propose a mechanism that drives the rise of market concentration and demonstrate how less-frictional international trade enables more efficient firms to be rewarded with greater market power. While many studies attribute the rise of superstar firms to the technological improvement (Antràs, 2020; Südekum et al., 2020), this paper attempts to investigate whether the emerging of global value chain and outsourcing process also favors the high-productivity firms and contributes to the rise of superstar firms.

The rest of the paper is organized as follows. Section 2 presents a general theoretical framework that encompasses monopolistic competition and variable markup to examine the impact of trade cost reductions on firms' markups and associated industrial resource reallocation. Section 3 describes the datasets and measurement methods used. Section 4 presents our econometric specifications and report the main results. Section 5 concludes our findings and contributions.

2. Theoretical framework

This section presents our theoretical framework on global sourcing, markup, and market concentration. Our model is based on and extends Melitz and Ottaviano (2008), Hornok and Muraközy (2019), Halpern et al. (2015), and Amiti et al. (2014). In line with the

⁴ Related studies with data from other countries include Fan et al. (2018) for China, De Loecker et al. (2016) for India, Altomonte and Barattieri (2015) for Italy, Moreno and Rodríguez (2011) for Spain, Konings et al. (2005) for Bulgaria and Romania and Harrison (1994) for Cote d'Ivoire.

previous models, our theoretical framework is based on a partial equilibrium analysis of only the commodity goods market. However, our theoretical framework extends the previous models by examining a long-run equilibrium where firms can enter and exit the market freely and the number of firms is determined endogenously. Using our theoretical framework, we examine the impact of input trade liberalization on industrial structure, such as the concentration of market power among firms and the entry and exit of firms. The remainder of this section presents the model and derives equilibrium prices, sourcing and exit strategies, marginal cost, and markups. We emphasize the importance of input-import penetration in a study of markups.

2.1. Consumers

Following Melitz and Ottaviano (2008), we assume consumers' preferences are defined over a continuum of differentiated varieties indexed by $i \in \Omega$, and all consumers share an identical quasi-linear utility function, i.e.,

$$U = q_0^c + \alpha \int_{i \in \Omega} z_i q_i^c di - \frac{1}{2} \gamma \int_{i \in \Omega} (z_i q_i^c)^2 di - \frac{1}{2} \eta \left(\int_{i \in \Omega} z_i q_i^c di \right)^2 \quad (1)$$

wherein q_0^c and q_i^c represent the quantities of the numeraire good and the differentiated variety i respectively; z_i denotes the quality level for the differentiate good i ; α , η , and γ are all positive parameters. The parameters α and η index the substitution pattern between the differentiated varieties and the numeraire good, and the level of competition intensity among differentiated varieties. The parameter γ indexes the decreasing rate of the marginal utility for each variety. we assume a unit constant substitution ratio between the product i 's quality and quantity, which allows us to simplify our analysis by combining the quality and quantity of each variety. Without loss of generality, our analysis is based on the measure of quality-adjusted quantity demand for each product i , which is defined as $Y_i \equiv z_i q_i^c L$. Following this setting, price level for the variety i is defined as the quality-adjusted price, i.e., $p_i \equiv \rho_i / z_i$, wherein ρ_i denotes the per unit price for variety i . Given the quality-adjusted price for variety i , consumers choose their quality-adjusted quantity on product i as:

$$Y_i \equiv L z_i q_i^c = \frac{\alpha L}{\eta N + \gamma} - \frac{L}{\gamma} p_i + \frac{\eta N}{\eta N + \gamma} \frac{L \bar{P}}{\gamma} \quad (2)$$

wherein L denotes the population of the economy; N measures the mass of varieties (which is also the number of active firms); and $\bar{P} = (1/N) \int_{i \in \Omega^*} p_i di$ is the aggregate quality-adjusted price index of all varieties in the market. The set Ω^* collects all the varieties that succeed to survive in the market, i.e., these varieties must satisfy the following condition:

$$p_i \leq \frac{1}{\eta N + \gamma} (\gamma \alpha + \eta N \bar{P}) \equiv p_{max} \quad (3)$$

In view of condition (3), all survived firms' prices should be up-bounded by the critical value p_{max} , otherwise their market demand will become zero. In next section, we will show that a variety's market price decreases in the firm's productivity level that produces it. Therefore, the lowest-productivity firms in the market will charge a price level at p_{max} to cover their high variable costs.

2.2. Producers

Similar to Amiti et al. (2014), we model the cost structure of the firm and the choice rule to use inputs from different sources. Assume there are two production processes. In the first stage, each firm produces intermediate inputs using labors or sources the intermediate inputs from the foreign countries.⁵ Consider firm i , indexed by its productivity level A_i , uses labor L_i and a composite intermediate input X_i to produce quality-adjusted output Y_i according to the following production function in the second stage:

$$Y_i = A_i X_i^\phi L_i^{1-\phi} \quad (4)$$

The composite intermediate input X_i consists of two sources of inputs, i.e., the domestic input and foreign input. D_i represents the quantity of the domestic-specific input which is produced by firm i , and M_i represents the quantity of foreign intermediate input which is sourced from foreign countries. In the first stage of production, to produce domestic input by amount of D_i/ω , firm i needs to hire L_i^m labors with the wage rate W , i.e., $D_i = \omega L_i^m$. The substitution elasticity between D_i and M_i is assumed as ξ .

$$X_i = \left[D_i^{\frac{\xi}{1+\xi}} + a M_i^{\frac{\xi}{1+\xi}} \right]^{\frac{1+\xi}{\xi}} \quad (5)$$

The productivity advantage of the foreign variety is measured by the parameter a . The love-of variety feature of the production function and the potential productivity advantage of imported inputs result in a cost-saving effect (efficiency improvement) from using

⁵ Here, we assume the domestic input is simultaneously produced by the firms that produce the final goods. Later, we discuss the robustness of our theoretical predictions by checking the situation where the domestic input is purchased from the domestic input producers.

both domestic and foreign inputs. The prices of imported and domestic inputs are denoted by P_M and $P_D = W/\omega$, respectively.

To import the intermediate input, firm i must incur a fixed cost f_i , which is assumed to be identical for all firms, i.e., $f_i = f_m$, for all i . The presence of such fixed costs has been empirically proven and widely assumed in theoretical frameworks (Amiti et al., 2014; Antràs et al., 2017; Gopinath and Neiman, 2014; Halpern et al., 2015)⁶. The firms are identified as importers/users of foreign inputs and non-importers. The cost index on intermediate inputs for importers and non-importers is computed as follows:

$$V_i = \begin{cases} \left[(P_D)^{-\xi} + a^\xi (\tau_m P_M)^{-\xi} \right]^{-\frac{1}{\xi}} & \text{importer} \\ P_D & \text{non-importer} \end{cases} \quad (6)$$

Here, τ_m captures the ice-berg cost of purchasing the foreign intermediates, including import tariffs, transportation costs, non-tariff barriers, and border effects, among others. Our aim is to estimate how the reduction trend in these costs could reshape the industrial structure and benefit the leading firms.⁷ By taking into account the cost structure, the use of a mix of domestic and foreign inputs will always reduce the cost of intermediate inputs. Firms that can import after paying the importing fixed costs will always mix domestic and foreign inputs as this strategy generates the lowest marginal cost. Without loss of generality, it is assumed that all firms face identical prices for both domestic and foreign inputs, i.e., $V_i^\phi = V^\phi$ for all firm i . Following the settings above, firm i 's production cost per quality-quantity unit is given by the equation:

$$c_i = \varsigma \varphi_i \left(\frac{W}{1-\phi} \right)^{1-\phi} \left(\frac{V_i}{\phi} \right)^\phi = \varsigma \varphi_i V_i^\phi \bar{D} \quad (7)$$

wherein W measures the domestic labor cost, and $\bar{D} \equiv [W/(1-\phi)]^{1-\phi} [V_i/(\phi)]^\phi$ is a common cost factor for both importers and non-importers; φ_i is the inverse productivity of firm i , i.e., $\varphi_i \equiv 1/(\varsigma A_i)$, wherein ς is a common parameter for all firms; and A_i is the productivity level for firm i . A greater value of φ_i means a lower value for A_i .⁸ The firms only differ in the inverse productivity level φ_i and the input cost index V_i . The inclusion of foreign inputs will always result in a lower marginal cost than using only domestic inputs. This cost-saving effect that implied by our settings for production function of aggregate input is consistent with empirical findings in a good deal of literature (Abreha, 2019; Amiti and Konings, 2007; Antràs et al., 2017; Bas and Strauss-Kahn, 2015; Blaum et al., 2018; Fan et al., 2018; Fan et al., 2015). The inclusion of foreign inputs or a reduction in importing cost τ_m will lower the per unit cost in terms of both quality and quantity spectrum. Given a certain quantity of output, a reduction in input costs directly reduces production costs. When foreign inputs contain high technologies, the cost-saving effect of foreign inputs manifests itself in the quality spectrum. Our study does not distinguish and analyze these two cost-saving channels in depth, and we hold an aggregate view that foreign input penetration leads to lower per unit cost c_i for the output measured by a combination of quality and quantity.

The profit maximization problem of firm i is given by:

$$\max_{p_i} \pi(p_i, c_i) = (p_i - c_i) Y_i \quad (8)$$

Profit maximization implies the results for firm i 's price p_i , markup μ_i , quality-adjusted output Y_i , revenue r_i , and profit π_i :

$$\left\{ \begin{array}{l} p_i = \frac{1}{2}(c_i + c_d) \quad (a) \\ Y_i = \frac{L(c_d - c_i)}{2\gamma} \quad (b) \\ r_i = \frac{L}{4\gamma} (c_d^2 - c_i^2) \quad (c) \\ \pi_i = \frac{L(c_d - c_i)^2}{4\gamma} \quad (d) \\ \mu_i = \frac{(c_i + c_d)}{2c_i} \quad (e) \end{array} \right. \quad (9)$$

When $c_i = c_d$, Eq. (9) implies $p_i = p_{max} = c_d$. c_d is the cut-off cost value (highest value) for the firms to survive the market. All firms with variable costs greater than this value will exit the market. Generally, markup is defined as ratio of price to marginal cost. It is for this reason that, in the markup equation, quality level z_i is multiplied by quality-adjusted price and cost. Based on Eq. (9), firm i 's markup μ_i decreases in its marginal cost c_i , which reveals a positive relation between the firm's productivity and markup.

⁶ The indirect empirical evidence for the existing of importing fixed costs include Abreha (2019), Elliott et al. (2019), Hornok and Muraközy (2019).

⁷ Antràs (2020) stresses this cost-reduction trend in trade of both inputs and final goods in the last decades.

⁸ We define the variable φ_i for the convenience of our theoretical discussions later.

2.3. Market equilibrium and impact of globalization

2.3.1. Determination of the importing productivity cutoff

We begin our analysis of market equilibrium in this section. Our focus is on how input imports affect the structure of the domestic market. Therefore, without loss of generality, we assume that all firms can purchase intermediate inputs from the foreign market and domestically, but only sell their products in the domestic market. We assume that the inverse productivity is drawn randomly from a known distribution, i.e., $\varphi \sim G(\varphi)$ with the definition range supporting $[\underline{\varphi}, +\infty)$. For simplicity, we keep the mass of entrants N_E and the productivity distribution $G(\varphi)$ fixed. The number of survived firms is thus given by $N = N_E G(\varphi_d)$ where φ_d is the cut-off value of the inverse productivity, i.e., $c_d = \zeta \varphi_d V_i^{\theta} \bar{D}$. Firm i decides whether to import the intermediate input based on the expected profit it faces. Then, we define $\Psi = \Psi_i \equiv \zeta V_i^{\theta} \bar{D}$ for all the importing firms and normalize $\zeta V_i^{\theta} \bar{D} = 1$ for all the non-importing firms. If importing the foreign input lowers the firm's variable cost, it must be such that $\Psi < 1$. The firm's decision on whether to use the foreign input depends on the comparison of the profits from using the foreign input and not using it. For convenience, we define the profit difference between an import decision and a non-import decision as $H(\varphi_i) \equiv \pi(\varphi_i|importer) - \pi(\varphi_i|non - importer)$, where $\pi(\varphi_i|importer) = (p_i^f - \varphi_i \Psi) Y_i^f - f_m$ with $\Psi < 1$ and $\pi(\varphi_i|non - importer) = (p_i^d - \varphi_i) Y_i^d$. Firm i will import the intermediate input only if $H(\varphi_i) > 0$. This choice rule is also presented in the Fig. 1, and summarized in Lemma 1 below.

Lemma 1. *Given the highest inverse productivity of the survived firms in the market and the following assumptions, i.e., (i) importing fixed cost f_m is identical to all firms, and (ii) the fixed cost satisfies the conditions $\underline{\varphi} > 2\sqrt{\frac{\gamma f_m(1+\Psi)}{L(1-\Psi)}}$, there exists three possible equilibrium cases: (i) in the range $\varphi_m \in [\underline{\varphi}, +\infty)$, there exists $H(\varphi_m) = 0$ such that $H(\varphi) \geq 0$ for $\varphi < \varphi_m$ and $H(\varphi) < 0$ for $\varphi > \varphi_m$; (ii) $H(\varphi) \geq 0$ for all firms existing in the market; and (iii) $H(\varphi) < 0$ for all firms that survive in the market.*

Lemma 1 implies that due to the fixed importing costs, only high-productivity firms are able to access to foreign inputs. The firms whose inverse productivity levels are higher than a critical value will not choose to import inputs. Specifically, this critic value is solved as:

$$\varphi_m = \frac{\varphi_d + \sqrt{\varphi_d^2 - \frac{4\gamma f_m(1+\Psi)}{L(1-\Psi)}}}{1 + \Psi} \tag{10}$$

Only the firms whose inverse productivity levels are lower than φ_m will self-select to import inputs (see illustration by Fig. 1 in Appendix).

2.3.2. Long-run equilibrium

This section concludes our theoretical framework by examining the characteristics of the long-run equilibrium. First, the number of firms N is endogenously determined by the mass of entrants N_E . Second, firms are not aware of their own inverse productivity information until they entering the market. As a result, firms will make an expectation of their future profits, and enter the market if they anticipate positive profits. Market entry stops only when the expected profit becomes zero, i.e., when the expected post-entry profit equals the entry cost f_E . Third, following the entry of firms and the determination of their productivity, the productivity cut-off φ_m to import and the productivity cut-off φ_d to survive in the market are determined by firms' optimal strategies to import and exit. Finally, the market price index \bar{P} is an aggregate of the prices charged by both importers and non-importers. Accordingly, the equilibrium variables can be determined by the following equations.

$$\left\{ \begin{aligned} & N = N_E G(\varphi_d) \quad (a) \\ & \int_{\underline{\varphi}}^{\varphi_m} \left[\frac{L(\varphi_d - \Psi\varphi)^2}{4\gamma} - f_m \right] dG(\varphi) + \int_{\varphi_m}^{\varphi_d} \frac{L(\varphi_d - \varphi)^2}{4\gamma} dG(\varphi) = f_E \quad (b) \\ & \varphi_m = \frac{\varphi_d + \sqrt{\varphi_d^2 - \frac{4\gamma f_m(1+\Psi)}{L(1-\Psi)}}}{1 + \Psi} \quad (c) \\ & \varphi_d = \frac{\alpha\gamma + \bar{P}\eta N}{\gamma + \eta N} \quad (d) \\ & \bar{P} = \int_{\underline{\varphi}}^{\varphi_m} \left(\frac{\Psi\varphi + \varphi_d}{2} \right) \frac{g(\varphi)}{G(\varphi_d)} d\varphi + \int_{\varphi_m}^{\varphi_d} \left(\frac{\varphi + \varphi_d}{2} \right) \frac{g(\varphi)}{G(\varphi_d)} d\varphi \quad (e) \end{aligned} \right. \tag{11}$$

Equation (a) of (11) features the determination of active firm number. Equation (b) represents the free-entry condition, where expected post-entry profits equal the entry costs. Equation (c) solves for the import critical value (see the derivative steps in Appendix).

Expected Profit Difference

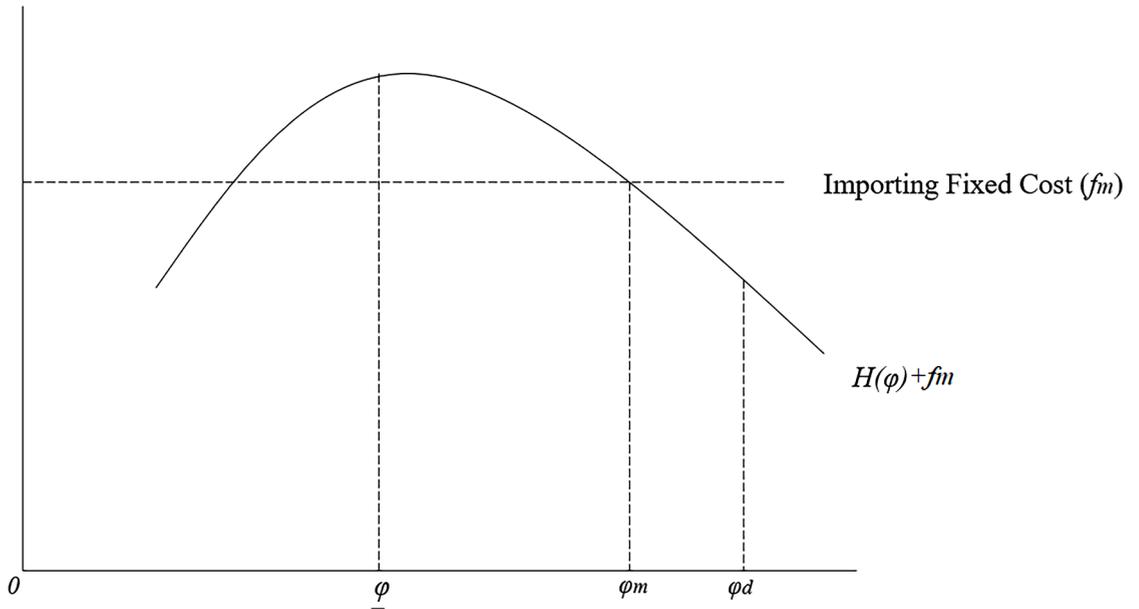


Fig. 1. Inverse productivity cut-off of importing firms.

Equation (d) is derived from the fact that the exiting firms at the margin have the highest marginal cost, i.e., $c_d = \varphi_d$, and charge the highest price among the surviving firms, namely, $p_{max} = (\alpha\gamma + \bar{P}\eta N)/(\gamma + \eta N)$.

Equation (c) reveals a positive relationship between φ_m and φ_d , given the value of Ψ . Based on equation (b), the value of φ_d only depends on the entry cost f_E and is independent of the firm number N . If we define equation (b), the condition for firms to enter the market, as the supply of firms, the curve which illustrates the supply of firms is drawn as a horizontal line in Fig. 2 (the curve S). Equation (d) determines the values for both N and φ_d . We define this equation as the demand of the firms, which is illustrated as the curve D . Obviously, when the trade cost Ψ decreases, the old demand curve D_0 shifts down to the position of the new demand curve D_1 , and the old supply curve S_0 shifts down to the position of the new supply curve S_1 . In this case, the inverse productivity φ_d decreases but the change in the cut-off value for the firm number N depend on the relative associated change of both the supply and demand

Inverse Productivity Cut-off

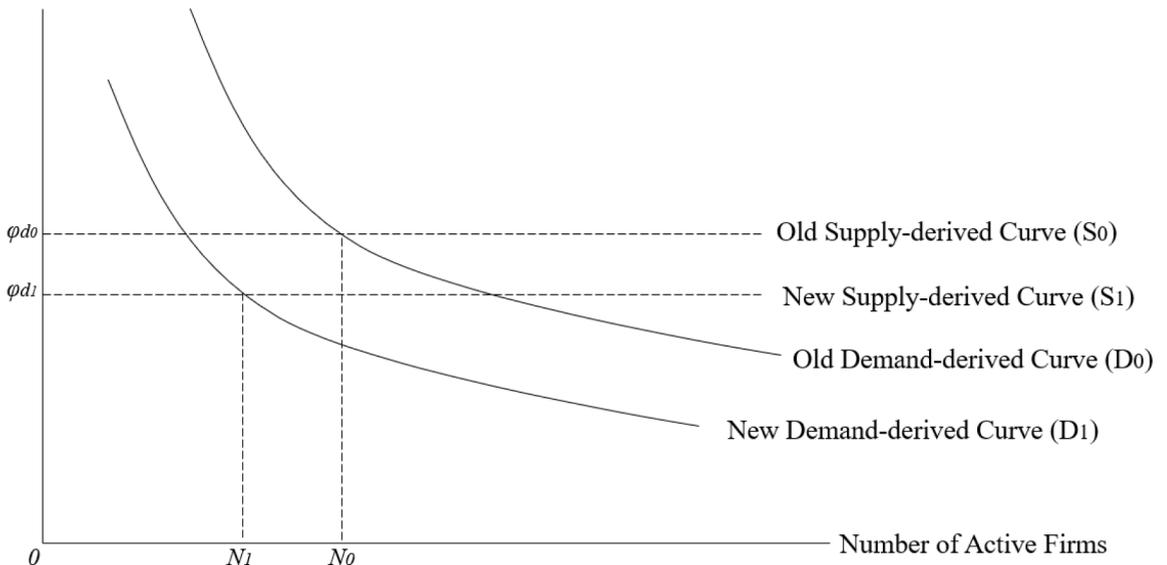


Fig. 2. Inverse productivity and firm number, endogenous entrants.

curves. When the values for both N and φ_d are determined, the massive of entrants N_E will be solved from the equation (a). For the case of long-run equilibrium, it is not easy to summarize the analytical proposition explicitly. As such, in the next section we will provide numerical examples of our arguments for changing each variable.

2.3.3. Industrial markup and productivity

In this section, we will compute the industrial level aggregate markups and decompose the effects that result in the changes of the markups. An industrial level simple average markup across all survived firms is given by:⁹

$$\bar{\mu}_s = \int_{\underline{\varphi}}^{\varphi_m} \left(\frac{\Psi\varphi + \varphi_d}{2\Psi\varphi} \right) \frac{g(\varphi)}{G(\varphi_d)} d\varphi + \int_{\varphi_m}^{\varphi_d} \left(\frac{\varphi + \varphi_d}{2\varphi} \right) \frac{g(\varphi)}{G(\varphi_d)} d\varphi \tag{12}$$

An example with the Pareto distribution $G(\varphi) = 1 - (\varphi/\varphi_m)^{-\alpha}$ is given by:

$$\bar{\mu}_s = \frac{1}{2} \left[1 + \frac{\alpha}{\alpha + 1} \frac{\left(\frac{1}{\Psi} - 1 \right) \left\{ \frac{\varphi_m}{\varphi_d} \left[\frac{\varphi_d}{\varphi_m} - \left(\frac{\varphi}{\varphi_m} \right)^{-\alpha} \right] \right\}^{-1}}{(1) \quad (2)} + \frac{\alpha}{\alpha + 1} \frac{\frac{1}{\Psi} \frac{\varphi_d}{\varphi} - \left(\frac{\varphi_d}{\varphi} \right)^{-\alpha}}{1 - \left(\frac{\varphi_d}{\varphi} \right)^{-\alpha}} \right] \tag{13}$$

Considering the Pareto distribution case of simple average markup, it is evident that the average markup $\bar{\mu}_s$ increases as the import critical value φ_m increases. Based on Eq. (13), we observe two channels for the rise in simple average markup because of the reduction of Ψ , i.e., the reallocation effect and cost reduction effects. Term (3) of Eq. (13) depicts the reallocation effect where lowering import costs reduces the surviving cut-off point φ_d , which in turn increases the intensity of high productivity firms in the market. Term (1) indicates that lower importing costs result in lower variable costs for importers directly, which enhances their ability to compete. Term (2) decreases in φ_m while increasing in φ_d . When more non-importing firms start to import (an increase in φ_m) and low productivity firms exit the market (a decrease in φ_d), the market competition intensity will become fiercer. Consequently, the markups of the non-importing firms will decline.

Next, we will show a sufficient condition for the simple average markup to increase in response to a lower importing cost Ψ . Based on equation (d) of (11), the change of φ_d will be very small in response to the varying of importing cost when the parameter η is small enough. If we set $\eta = 0$, φ_d will keep constant to the change of importing cost Ψ . Given this property, when the importing cost Ψ decreases, the importing critical value φ_m will increase according to Eq. (10). This change will induce more firms to use the imported inputs. Given all these properties and the fact that $1/\Psi - 1 > 0$, Eq. (13) implies a positive relationship between φ_m and $\bar{\mu}_s$. In addition, from Eq. (12), we observe that a reduction in Ψ directly increases the value of $\bar{\mu}_s$ and an increase of φ_m will enhance such positive effect. Therefore, when the parameter η is small enough (not necessary to be zero), the simple average markup $\bar{\mu}_s$ will decrease in Ψ . The sales-weighted average markup is derived as:

$$\bar{\mu}_w = \int_{\underline{\varphi}}^{\varphi_m} \frac{L[\varphi_d^2 - (\Psi\varphi)^2]}{4\gamma S(\Psi)} \left(\frac{\Psi\varphi + \varphi_d}{2\Psi\varphi} \right) \frac{g(\varphi)}{G(\varphi_d)} d\varphi + \int_{\varphi_m}^{\varphi_d} \frac{L[\varphi_d^2 - \varphi^2]}{4\gamma S(\Psi)} \left(\frac{\varphi + \varphi_d}{2\varphi} \right) \frac{g(\varphi)}{G(\varphi_d)} d\varphi \tag{14}$$

where the total sales of all firms are $S(\Psi) \equiv \int_{\underline{\varphi}}^{\varphi_m} \frac{L[\varphi_d^2 - (\Psi\varphi)^2]}{4\gamma} \frac{g(\varphi)}{G(\varphi_d)} d\varphi + \int_{\varphi_m}^{\varphi_d} \frac{L[\varphi_d^2 - \varphi^2]}{4\gamma} \frac{g(\varphi)}{G(\varphi_d)} d\varphi$.

The sales-weighted average markup is more complex than the simple average markup because it takes into account market shares between importing and non-importing firms in addition to the three transmission channels mentioned earlier. The market share of the

importing firms can be calculated using the equation $M_{im}(\Psi) \equiv \int_{\underline{\varphi}}^{\varphi_m} \frac{L[\varphi_d^2 - (\Psi\varphi)^2]}{4\gamma S(\Psi)} \frac{g(\varphi)}{G(\varphi_d)} d\varphi$, while the market share for the non-

importing firms is given by $M_{non}(\Psi) \equiv \int_{\varphi_m}^{\varphi_d} \frac{L[\varphi_d^2 - \varphi^2]}{4\gamma S(\Psi)} \frac{g(\varphi)}{G(\varphi_d)} d\varphi$. Eq. (14) reveals the fact that non-importing firms lose market share

when the importing cost Ψ decreases. This is because the parameter φ_d also decreases when Ψ decreases. When importing costs decrease, it leads to the exit of the lowest-productivity firms and the size-shrinking of non-importers, both of which contribute to market concentration on the high-productivity (high-markup) firms. Furthermore, a lower importing cost Ψ leads to a greater number

⁹ The details of the derivation are presented in Appendix.

of firms beginning to import, which in turn leads to higher markups for those firms. It is possible to obtain a closed-form solution for the weighted average markup, but we will also provide an example of numerical simulation to illustrate changes in the weighted average markup.

To better demonstrate our theoretical analysis and achieve a practical outcome, we assign real values to the parameters in the market equilibrium equations that determine the long-run outcome. We set the following parameter values: variable importing cost $\Psi \in [0.45, 0.52]$; $\gamma = 1$; $F_m = 7$ and $F_e = 3$; $L = 100$; $\alpha = 2.5$; $\eta = 1$; $\underline{\varphi} = 0.5$; and $\bar{D} = 1$. Based on these parameter values, we predict the following outcomes in response to a reduction in importing marginal cost:

The market surviving critical value, φ_d , decreases. The critical value for importing, φ_m , increases. The number of firms in the market, N , decreases. The overall price level, \bar{P} , decreases. The average markup increases (referee to Figs. 3 and 4 for details).

Based on our simulation, we make the following testable predictions regarding changes in the market resulting from a reduction in marginal import costs:

1. High-productivity firms are more likely to self-select to the international sourcing market.
2. High-productivity firms will gain higher markups in response to a reduction in marginal input-trade cost.
3. High-productivity firms will gain more market shares, while low-productivity firms will lose market shares in response to a reduction in marginal input-trade cost.

2.4. Discussion on the case of sourcing from domestic input producers

In our primary text, we assume that U.S. firms either use imported inputs or produce the inputs themselves. In cases where firms produce domestic inputs, the departments responsible for this production are fully integrated with downstream departments. If the productivity and wage rates for producing domestic inputs do not change, the markups charged by firms will only depend on the difference between the input and product prices. However, if some firms do not produce intermediate inputs themselves, instead purchasing them from domestic firms that produce these inputs, the change in aggregate markup will depend not only on markup adjustments made by firms using intermediate inputs, but also by domestic firms producing intermediate inputs. A decrease in the price of imported inputs may lead importing firms to substitute domestic inputs with foreign inputs, thereby increasing competition pressure on domestic input producers. A decline in demand for domestic inputs will result in a reduction of markups charged by domestic input producers.

Our estimations at the industrial level regarding markup show that coefficients on HIMP are negative but insignificant, indicating that the cost-saving effect of VIMP dominates the competition effect revealed by the HIMP indicator. Firm-level estimations also show a much higher elasticity of VIMP than HIMP. Our theoretical framework explains this result based on the specification of importing firms' demand function for foreign and domestic inputs, i.e., the formula (5), which features a production pattern where both foreign and domestic inputs are simultaneously substituted and complemented.

When the price of imported inputs declines, it will have two consequential effects on the demand for domestic inputs. The first effect is a substitution effect triggered by the decrease in relative price of imported inputs. This effect leads to a decline in demand for domestic inputs and a reduction in the markups of domestic inputs. The second effect is the scale effect, where importing firms benefit from the reduction in marginal costs due to intermediate input trade liberalization. Their market demand will increase, leading to increased production scale and a corresponding increase in demand for domestic inputs. If the demand elasticity is large enough in the commodity goods market, and the substitution ratio between domestic and foreign inputs is small enough, then the substitution effect on domestic inputs will be offset by the complementary effect. Under these conditions, the net effect of input trade liberalization on demand for domestic inputs will be mute or even positive. Detailed proof steps are shown in the appendix.

3. Data and measurement

Based on our theoretical framework, we demonstrate that a decrease in trade costs and the resulting increase in input import penetration are related to an increase in the markup. We attribute this result to both a reduction in production marginal costs and a reallocation of resources. The remainder of this paper seeks to provide empirical evidence for this claim. To identify the relationship between input import penetration and markups, we use Compustat data for publicly listed firms in the United States to generate markups, and we combine U.S. trade data and input-output tables to analyze the impact of input import penetration on markups. Three types of data are used in the empirical study: balance sheet data from firms, industry-level trade data, and input-output tables at the commodity level. The statistic characteristics of our key variables are demonstrated in Table 1.

3.1. Firm balance-sheet data

We use Compustat (North America) Fundamental Annual database to derive firm-level balance sheet information. Compustat has variables that are needed for production function estimation including annual sales, wages, capital stock, as well as the labor of all the US publicly listed firms available from 1950 to 2014 in Wharton Research Data Services (WRDS). We restrict the sample as follows: Firstly, we only consider and identify firms incorporated in the United States based on Stock Exchange Code (EXCH) and Foreign Incorporation Code (FIC); Secondly, we exclude observations with obviously mis-measured variables of interests, such as negative sales or employment. The common GDP deflator is retrieved from the Bureau of Economic Analysis's National Income and Product

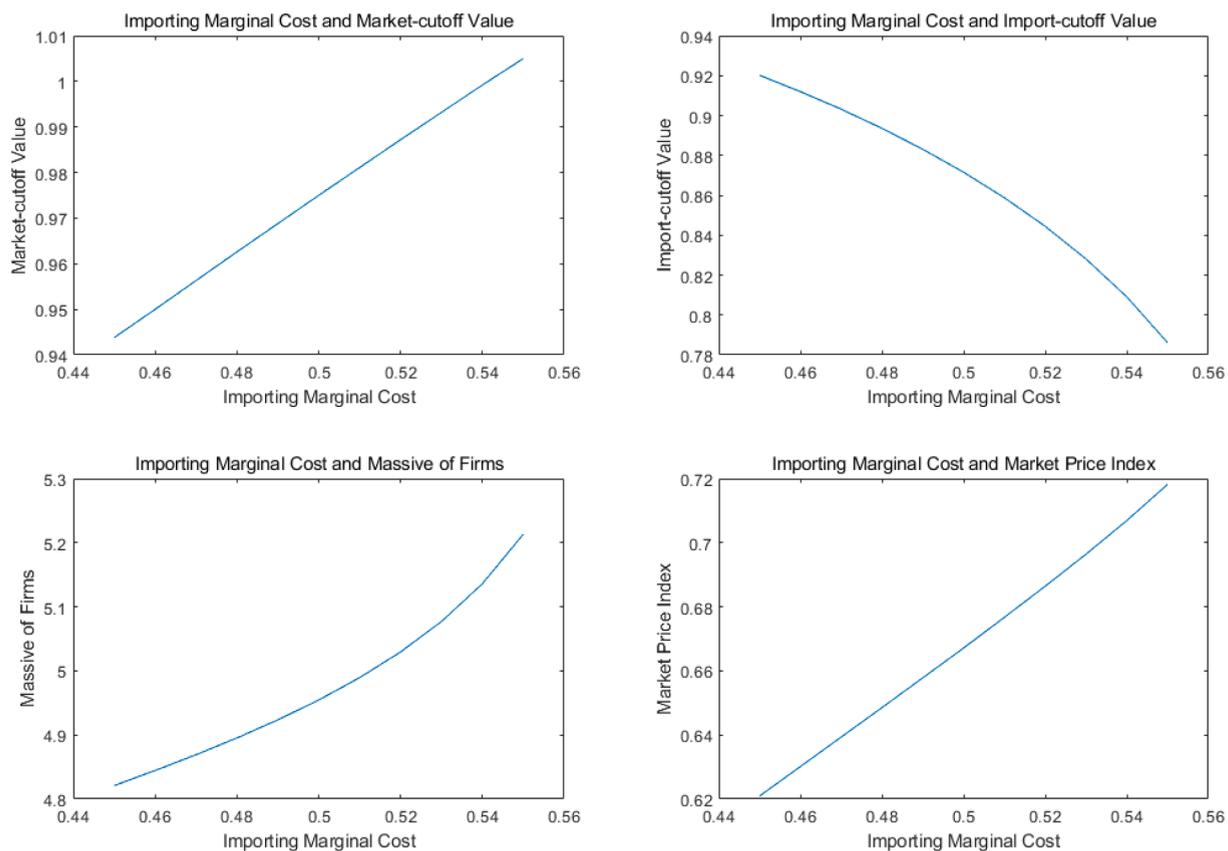


Fig. 3. Importing marginal cost and markup equilibrium outcomes.

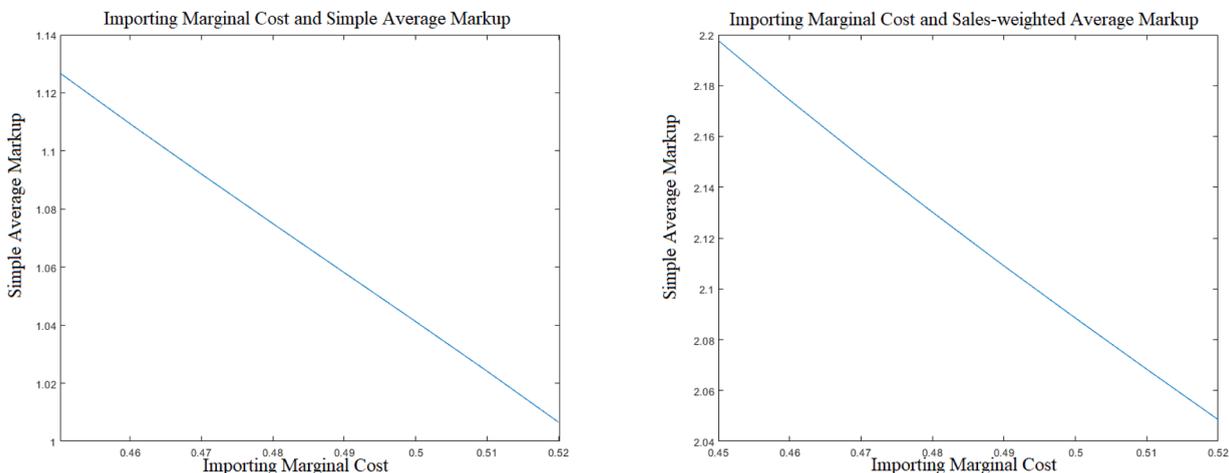


Fig. 4. Importing marginal cost and average markup.

Accounts (NIPA) tables of the United States. Therefore, we obtain firm-level markup by applying the so-called cost-based production approach as in [De Loecker and Warzynski \(2012\)](#).

Our analysis focuses on the sample from 1977 to 2014, that we match with industrial level import penetration ratios in the firm-level regression. It reduces our sample to 209,476 firm-year observations with an average of 5512 firm-level observations per year. Compustat assigns each firm a North American Industry Classification System (NAICS) 2012 6-digit sector code based on the firm's operation reported as required by Financial Accounting Standards Board (FASB). The 2012 NAICS codes have 1065 disaggregate industries. To match it with the industrial classification in the Input-Output table, we first converted the different versions of NAICS

codes to the 2007 version and then assigned each 2007 NAICS code with one of the 389 6-digit IO industries used in the Input-Output table from Bureau of Economic Analysis (BEA). [Table 2](#) shows the IO industrial distribution of the firm-year observations at the most aggregate level between 1977 and 2014.

The Compustat dataset permits us to estimate firm-level markup through 38 years by using the production approach, but there could be a problem of mismatch between our theory and the empirical results because of sample selection. Our theory computes the average markup over the entire productivity distribution of the firm. COMPUSTAT, on the other hand, includes only publicly traded companies, which, on average, are larger, older, more capital intensive, and engage in a greater number of international transactions than their privately held counterparts. In addition, we are interested in how imported inputs penetration is related to markup at the firm level, but Compustat does not contain information on how much each firm employ foreign inputs. Therefore, in the industry-level regression, we compute the sales-weighted markup at the 6-digit BEA I-O industry level to match with industry-level import penetration measures. That said, it is important to note that our sample still covers firms across most of the industries and matches closely with the industrial distribution across the whole economy. For instance, a large portion of firms are in the Manufacturing and Finance sector, accounting for 35.5% and 21.8% of the observations respectively in the sample. Lastly, to further deal with the selection from the publicly traded firms, we leverage the population weights of each sector to adjust the weights in the Compustat sample in the spirit of [De Loecker et al. \(2020\)](#). In this way, we try to minimize the potential bias from the difference in sectoral composition between Compustats and the whole firm population.

3.2. Measurement of markup

Defined as the ratio of price over marginal cost, markups can be estimated by a few different methods prevailing in the field of empirical industrial organization. As detailed data on price and marginal cost data is usually unavailable, markup estimation depends on the granularity of the available data and the choice of assumptions. On one hand, the “demand-based” estimation requires assumptions on the form of demand function and market structure, therefore marginal cost and markups are estimated with the associated demand elasticity and firms’ optimal pricing behavior as in [Bresnahan \(1982\)](#) and [Berry et al. \(1995\)](#). On the other hand, the “production based” method proposed in [De Loecker and Warzynski \(2012\)](#) builds upon the insight of [Hall \(1988\)](#) where markups are inferred by estimating the production function with assumptions on the firms’ optimal input choice from total cost minimization. Markup is then derived as the product of the input revenue share and output elasticity of any chosen variable input. Intuitively, it is measured as technology-adjusted cost share. As the input cost shares are often available in the accounting data, it is easy to estimate markup by adding an estimate of the input elasticity. The input elasticity is estimated using various production function estimation methods including the OLS, Olley–Pakes, and Levin–Pettrin methods. And our baseline results are based on Olley–Pakes method.

We adopt the “production-based” method in our markup estimation for several reasons. Firstly, one of our model predictions is that imported input penetration is associated with rising markup through the change of market structure. Therefore, it is reasonable to impose as least assumptions as we can on the market structure in markup estimation. Secondly, Compustat data is firm-level balance sheet accounting data, from which input share is directly calculated. Lastly, following the same method of markup estimation would make our results comparable to [De Loecker et al. \(2016\)](#). As we are following the same manner, we relegate the necessary derivation of markup in the Appendix.

3.3. Trade data

The trade data are used to compute direct import penetration measures. The data is divided into three parts: 1977–1988; 1989–2006; and 2007–2014. The first two parts of data come from U.S. trade data assembled by [Feenstra \(1996\)](#). For the period 1977 to 1988, the data are by year at the level of 4-digit 1972-revision SIC industry and the level of 1987 SIC version for the years from 1989 to 2006.¹⁰ The other part of trade data comes from USA Trade Online, which contains the data on the U.S. (down to district-level) export, import, and total trade value at various industrial classification such as 10-digit HTS and 6-digit NAICS for different versions covering from 2007 to 2014. USA Trade Online always starts using the new NAICS revision the year after the change. For 2008–2012, the data report the 2007 NAICS codes and for 2013–2017 the 2012 NAICS codes and so on. To match with other sources of data, we harmonized the different industrial classifications and different versions based on the concordance table provided by the Census Bureau and Bureau of Economic Analysis.

3.4. Input-output table

A crucial component of our empirical analysis is the derivation of a measure of import penetration of intermediate products or vertical import penetration. To build this measure, we take advantage of input-output tables that provide information on the level of interdependence and input use between industries. All the industry and I-O data are retrieved from the Bureau of Economic Analysis (BEA) of the U.S. Department of Commerce. The I-O tables along with industry economic accounts provide detailed information on the interrelationships between producers and users and the contribution to production across industries. The data are available at three levels: sector (15 industry groups), summary (71 industry groups), and detail (389 industry groups). To get the highest level of

¹⁰ There are 533 unique 4-digit SIC 1972 version industries appear in the 1977-1988 sample, converted to 507 NAICS 2007 industry codes. For 1989-2006 sample, there are 459 unique SIC 1987 version industries converted to 456 NAICS 2007 industry codes.

Table 1
Summary statistics.

Variables	Mean	S.D.	Min.	Max.	Obs.
Markup	1.634	1.103	0.012	23.622	209,476
HIMP	0.156	0.253	0	1	168,022
VIMP	0.168	0.221	0	1	168,022
ln(sales)	11.464	2.483	0	19,996	209,476
ln(Capital)	10.907	2.655	-0.084	19,939	208,374
ln(labor)	-0.303	2.291	-6.907	7.696	186,404
ln(profit margin)	-1.488	0.139	-1.869	-1.302	209,476
ln(cost of goods sold)	10.937	2.522	0	19,892	209,476
HHI	0.207	0.204	0.013	1	209,476

Notes: The table reports the summary statistics for the main independent and dependent variables used throughout the empirical analysis. Markup is estimated firm-level markups by [Olley and Pakes \(1996\)](#) method. Horizontal and vertical import penetration ratios are calculated by the methods described in [Section 3](#) using weights from 1977 BEA I-O benchmark table.

Table 2
Sample firm distribution by broad industry.

IO code	Industry description	Firms	Freq(%)
11	Agriculture, forestry, fishing, and hunting	1513	0.4
7	Arts, entertainment, recreation, accommodation, and food services	10,132	2.5
23	Construction	5824	1.4
6	Educational services, health care, and social assistance	6924	1.7
FIRE	Finance, insurance, real estate, rental, and leasing	89,734	21.8
51	Information	35,155	8.5
31G	Manufacturing	146,914	35.6
21	Mining	32,971	8
81	Other services, except government	1624	0.4
PROF	Professional and business services	21,838	5.3
44RT	Retail trade	17,374	4.2
48TW	Transportation and warehousing	10,572	2.6
22	Utilities	18,015	4.4
42	Wholesale trade	13,941	3.4
	Total	412,565	100

Notes: The table reports the industry distributions for the firms in the firm-level data from Compustats from 1977 to 2014. The IO Code is based on BEA industry classification at sector level.

disaggregation, we make use of the I-O data at a detail level that is available for each 5 benchmark years between the period 1977–2007. We calculate the weights by measuring how much each industry's production is relying on the products of another sector by the use values shares of the industry pair appear in detail I-O use table in 1997 (the middle year of our sample) in the baseline regression. For example, the weight d_{js} represents the value share of the input used by industry s from industry j of the total inputs utilized by industry s in the benchmark year, i.e., $d_{js} = \frac{use_{js}}{\sum_{j \in S} use_{js}}$.

3.5. Measures of import penetration

This section describes how our main import penetration variables are constructed. We look at the impact of import penetration in both the direct and indirect channels. Horizontal import penetration measures the direct effect of imported product and within-sector competition. By contrast, vertical import penetration takes the interdependence and input usage among sectors into consideration. Horizontal and vertical import penetration is measured for the period 1977–2014 and each of the 389 benchmark I-O industries based on the 1997 benchmark I-O table classification.

The horizontal import penetration (HIMP) for industry s in year t is calculated as:

$$himp_{st} = \frac{imp_{st}}{imp_{st} + prod_{st} - exp_{st}} \quad (15)$$

where imp_{st} is the value of imports from the world to the US in industry s at time t , and $prod_{st}$ is the production value of industry s in year t .

Similar to the way of separating input tariffs from output tariffs in [Amiti and Konings \(2007\)](#), we measure the cumulative impact of foreign input penetration in the industry s that is supplied by sector j by defining a measure of vertical import penetration ratio (VIMP). We define this for industry s as the weighted average of the import penetration of its inputs:

$$VIMP_{st} = \sum_j d_{js} HIMP_{jt} \quad (16)$$

wherein $HIMP_{jt}$ is the ratio of imported goods to the total goods in industry j . d_{js} is the usage ratio of intermediate inputs coming from industry j that used by industry s . The detailed for the computation method for d_{js} is described in Section 3.4 above. Table 3 shows the varying changes in VIMP across U.S. sectors during the observation period, which are ranged from 0.04 to 0.47.

Horizontal and vertical import penetrations make different impacts on both firms' marginal costs and markup. On one hand, higher HIMP leads to higher competition intensity, and as a result lowers firms' markups. On the other hand, deepening of the VIMP will not influence the competitive environment directly, but reduces the importing firms' marginal cost. If the cost reduction is not fully pass-through with the price adjustment, the importing firms' markups will increase. As the rise of importing firms' market power, the non-importing firms will face higher market competition and lose the market share. In aggregation, a rise of the VIMP ratio will lead to an increase of the industry's average markup.

4. Empirical investigations

In this section, we perform empirical estimations to test the main predictions of our theoretical model, i.e., the VIMP is positively associated with average markups across industries and over time. We estimate our baseline specification at the industry level and firm level respectively for a full combined sample from the years 1977–2014.

4.1. Stylized facts

We start by presenting how average markup increases with import penetration across the US economy in the last four decades. Fig. 5 illustrates the timeline evolution of import exposure along with the sales-weighted average of markup. Measured as the value of imports of goods and services to GDP, the import exposure ratio has been steadily increasing in the first and half decade (1960s–1970s) despite the slightly drop of markup in the same period. Following the sharp increase in import exposure since 1970, the markup has been increasing in the next decades, from the late 1970s till the present. As noted by De Loecker et al. (2016), there has been a sharp rise in the markup from around 1.2 in the late 1970s to around 1.6 in 2014, while the import exposure ratio has doubled in the same period: it increases from around 10% in 1980 to 20% in 2014. This figure suggests that import exposure may have changed markup in some ways other than only output competition.

In Fig. 6, we report the VIMP ratio calculated as described in Section 3 with average markup from 1977 to 2014. Recall that the VIMP ratio is the average of direct import penetration ratio in each industry (HIMP), weighted by the ratio of how each industry uses the other industry's output in the production. The VIMP ratio thus indicates the import penetration ratio of input. Remarkably, the pattern of VIMP is very much aligned with the average markup since 1970s. On average, it increased from 0.05 to over 0.2 up to 2014. Fig. 7 shows that markup distribution becomes more and more dispersed between 1980 and 2014. This change pattern is consistent with our theoretical prediction that high-productivity firms gain more market power while the low-productivity firms lose market power in the past four decades due to the globalization of production processes. These figures provide suggestive evidence consistent with predictions in the theoretical model. Next, we show the empirical test of these conjectures.

Fig. 8 shows the sector level correlation between VIMP/HIMP and change of markup. We observe a roughly positive correlation between VIMP and markup, while a negative correlation between HIMP and markup with the full sample.

4.2. Import penetration and adjustment of aggregate markup

With the import penetrations and industry level markup measures in hand, we can implement the following regression model (17).

$$\ln Markup_{st} = \beta_1 HIMP_{st-1} + \beta_2 VIMP_{st-1} + X'_{st} \gamma + \sigma_s + \delta_t + \varepsilon_{st} \quad (17)$$

where $\ln Markup_{st}$ is the log estimated average markup (either sales-weighted average or simple average across all firms within each industry) in the 6-digit US Input-Output industry s weighted by sales in year t . $HIMP_{st-1}$ and $VIMP_{st-1}$ are the horizontal and vertical import penetration ratios in the same sector s . They are lagged for one period to accommodate the time it takes to adjust markups accordingly as described in the model and they also serve to attenuate potential simultaneous bias between import penetration and markup. X_{st} is a vector of industry-level control including industrial level capital-labor ratio, sales, and HHI. σ_s and δ_t capture the industry and time fixed effects, respectively, which control for the time-invariant industry-related and time effects. ε_{st} is the error term. We clustered the standard errors at the industry level in our following regressions to accommodate non-independent residuals across observations within industries. Based on our theoretical framework, we expect β_2 to be significant and positive.

Table 4 reports the baseline regression results for sales-weighted average markup across all firms within each industry. The results with all sectors show that a rise of 10% point in the VIMP is associated with around 3.4% increase in the aggregate markup. When we estimate the sub-samples that are grouped as manufacturing and service sectors, we find that the coefficients on VIMP are significant and positive with both the manufacturing and services samples. In the manufacturing sectors, a 10% point increase in the VIMP is associated with around 1.7% increase in the markup, while in the service sectors, the number is 3.9. These results suggest a net positive effect of VIMP and HIMP together on industrial aggregate markup.

As indicated by Edmond et al. (2023), the sales-weighted average markup may over-estimate the value of the industrial level aggregate markup. To address this potential issue, we also perform the sector-level estimations using the industrial cost-weighted average markup, where the weight is set as each firm's direct cost of goods sold (COGS).

Table 5 reports the relevant estimation results with COGS and shows a significantly positive effect of VIMP on markup. According to

Table 3
Change of import penetration ratios in manufacturing sectors: 1980–2014.

Industry code	Industry description	Δ HIMP	Δ VIMP
311FT	Wood products	0.060	0.139
313TT	Nonmetallic mineral products	0.252	0.133
315AL	Primary metals	0.187	0.101
321	Fabricated metal products	0.849	0.403
322	Machinery	0.110	0.131
323	Computer and electronic products	0.081	0.287
324	Electrical equipment, appliances, and components	0.064	0.170
325	Motor vehicles, bodies and trailers, and parts	0.059	0.040
326	Other transportation equipment	0.026	0.329
327	Furniture and related products	0.125	0.139
331	Miscellaneous manufacturing	0.052	0.210
332	Food and beverage and tobacco products	0.090	0.271
333	Textile mills and textile product mills	0.111	0.252
334	Apparel and leather and allied products	0.098	0.146
335	Paper products	0.145	0.315
3361MV	Printing and related support activities	0.204	0.372
3364OT	Petroleum and coal products	0.162	0.108
337	Chemical products	0.113	0.260
339	Plastics and rubber products	0.038	0.470

Notes: The table reports the change of calculated horizontal and vertical import penetration ratios for manufacturing sectors at BEA industry classification summary level, 1980–2014, taking 1997 Input Output table as benchmark.

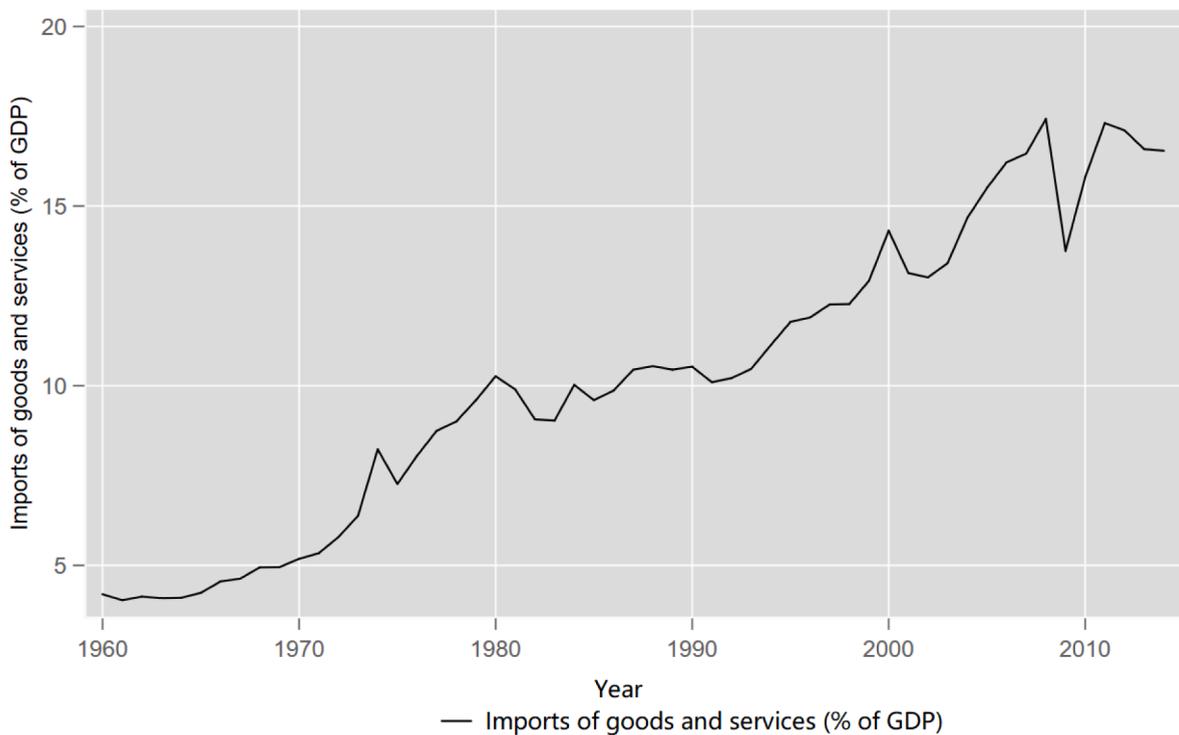


Fig. 5. The evolution of import to GDP ratio in the U.S. (1960–2014).

Table 5, a rise of 10% point of VIMP is associated with around 3.6% increase in industrial markup. When estimating with the sub-sector samples, we find a 10% point rise of VIMP leads to around 1.5% increase in the markup in the manufacturing sectors, while an around 4.2% increase for the service sectors.

Based on the results from **Tables 5** to **6**, we observe a mute effect of HIMP on markups in manufacturing sectors while a significantly positive effect in service sectors. There is a significant share of imported final goods in the U.S. traded within firms (**Brainard, 1997**). We suppose these results are due to the intra-firm trade or the outsourcing of the final assembling process by the multinational corporations. Firms move their production processes overseas to reduce the variable production costs and then re-import the final goods to the home market, e.g., the Apple Inc. moves the assemble process to China and re-imports the final products, which saves the



Fig. 6. The evolution of average markups and imported input penetration in the U.S. (1974–2014).

production costs for the company. Therefore, we observe a positive correlation between the HIMP and the markups, which offsets the competition effect of HIMP.

Table 6 reports the baseline regression results for the simple average markup across all firms within each industry. The results show a lower markup-elasticity of VIMP. For example, the coefficient on VIMP for the simple average markup is 0.227, which is significantly lower than the coefficient (0.339) in the regression for the sales-weighted average markup. Moreover, the coefficient on the VIMP is insignificant for the manufacturing sectors sample. These results suggest that the adjustments on the market shares between the high- and low-markup firms should be accounted as an important factor that contributes to the rise of sales-weighted average markup. Based on the coefficient $\hat{\beta}_2$ that estimated from Column 2 of Table 4, we approximate the contribution ratio of the rise of VIMP on the increment of markup during the period 1977–2014 based on the formula (18) below.

$$CR_{VIMP} \equiv \frac{\Delta Markup_{1997-2014,S}}{\Delta Markup_{1997-2014,R}} = \frac{\left\{ \sum_j [(Markup_{j,1997} + \hat{\beta}_2 \times \Delta VIMP_{j,1977-2014}) \times (S_{j,1977} + \Delta S_{j,1977-2014}) - Markup_{j,1977} \times S_{j,1977}] \right\}}{\Delta Markup_{1997-2014,R}} \quad (18)$$

wherein $\Delta Markup_{1997-2014,S}$ is the estimated change of aggregate sale-weighted average markup between 1977 and 2014 that induced by the rise of VIMP; $\Delta Markup_{1997-2014,R}$ is the real change of aggregate sale-weighted average markup between 1977 and 2014; $Markup_{j,1977}$ and $S_{j,1977}$ are the aggregate markup and market share for industry j in the initial year 1977; $\Delta VIMP_{j,1977-2014}$ and $\Delta S_{j,1977-2014}$ are the changes of VIMP and market share for industry j in the period 1977–2014. An approximated result shows that the rise of VIMP contributes to around 17% increment of aggregate markup in the period 1977–2014.

4.3. Adjustment of markup within firms

In the previous section, we have shown that industrial average markup increases in response to a rise of imported inputs penetration ratio. In this section and Section 4.4, we will decompose the change of aggregate markup by exploring how the markup is adjusted within each firm and across firms through resource reallocation toward the high-markup firms. As argued by Autor et al. (2020), the increase in aggregate markup can be decomposed by the markup adjustment within firms and the market concentration towards the firms with relatively high markups. The relevant results will unveil the adjustment-elasticity of markup within each firm.

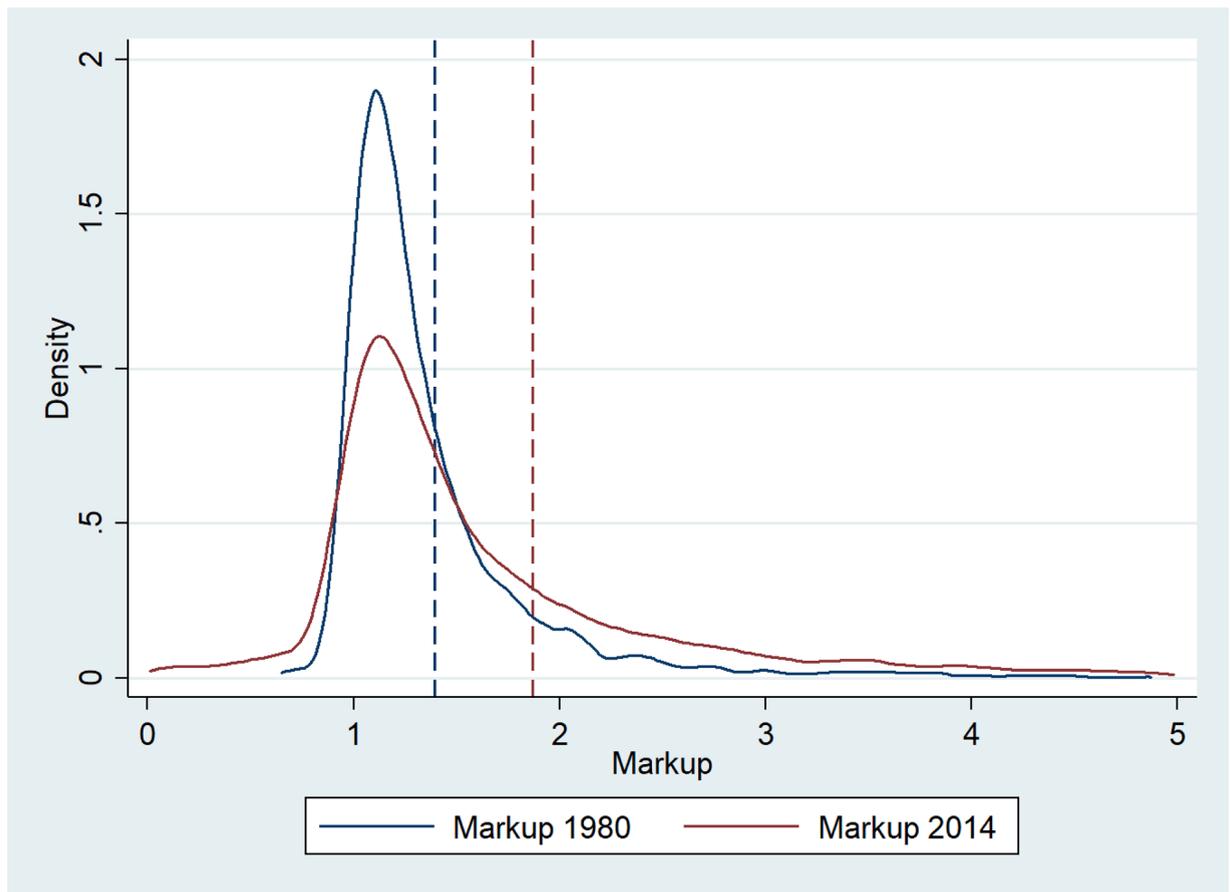


Fig. 7. A comparison of markup distributions between 1980 and 2014.

In particular, we regress firm-level markups over 6-digit industrial import penetration ratios as in [Acemoglu et al. \(2016\)](#) and [Olper et al. \(2017\)](#),

$$\ln Markup_{ist} = \beta_1 HIMP_{st-1} + \beta_2 VIMP_{st-1} + F_{it}'\gamma + \theta_i + \delta_t + \varepsilon_{st} \quad (19)$$

wherein $\ln Markup_{ist}$ is the log of markup of the firm i , who operates in industry s at year t in model (19).¹¹ The firm characteristic vector F_{it} is added to account for time-variant firm-level factors including the total sales, capital-labor ratio, productivity, and industry's HHI that could also influence a firm's capacity of adjusting markups. We also include firm fixed-effects as captured by θ_i , and year fixed-effects as captured by δ_t . Our results are robust to alternative specification of markup, e.g., absolute value of markup or profit margin (profit ratio over sales).¹²

[Table 7](#) reports the results from the firm level regressions without control variables in column (1) and with controls as in model (19). Similarly, we find a strongly significant and positive correlation between imported inputs penetration ratio (VIMP) and the value of markup, while a significantly negative correlation between imported output inputs penetration ratio (HIMP) and the value of markup.

We further look deeper into the effects on manufacturing sectors and service sectors in columns (3) through (4) for parallel specifications in [Table 7](#) respectively. We find that a significantly positive effect of imported inputs penetration on the markup in both sectors. The effect of penetration of imported final goods is significantly negative for manufacturing sector, but mute for the service sector. The scale of the coefficients on VIMP (imported inputs penetration) ranges from 0.051 to 0.077, which is much smaller than the sector-level estimation with the aggregate markup. This result suggests that the rise in aggregate markup is largely driven by the resource-reallocation effect toward the high-markup firms.

¹¹ In these regressions, we still use the industrial level data for the variables horizontal and vertical penetration ratios due to the lacking of firm level data for these variables.

¹² We also perform the IV estimations in line with the method in [Autor et al. \(2013\)](#). The results are consistent with our baseline estimations.

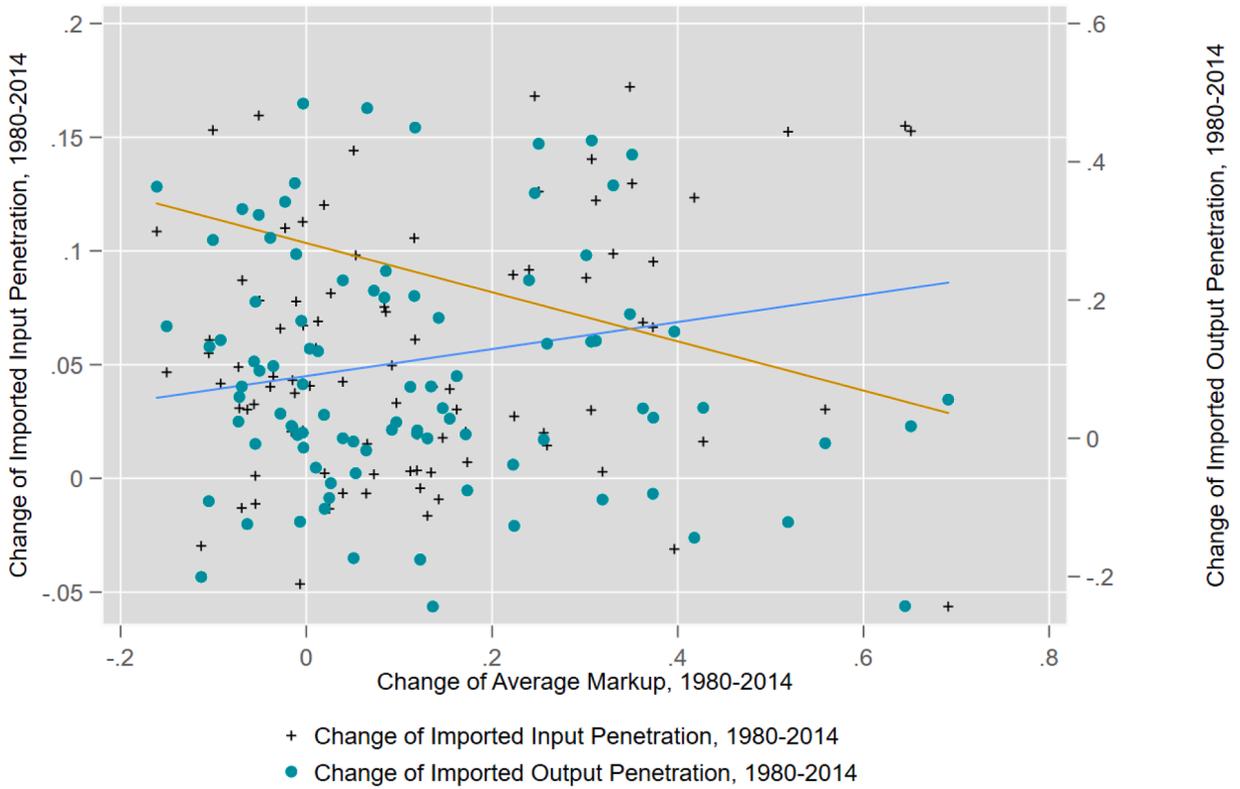


Fig. 8. The change of average markups and the change in import penetration in the U.S. (1980–2014).

Table 4

Sector-level sales-weighted average markup.

Dependent variable	<i>lnMarkup</i>		Manufacturing (4)	Services (6)
	All sectors (1)	(2)		
$VIMP_{t-1}$	0.335*** (0.115)	0.339*** (0.110)	0.170* (0.096)	0.393*** (0.124)
$HIMP_{t-1}$	-0.116 (0.072)	-0.086 (0.067)	-0.023 (0.038)	0.776*** (0.133)
Other controls	NO	YES	YES	YES
Industry FEs	YES	YES	YES	YES
Year FEs	YES	YES	YES	YES
Observations	9771	9724	6826	2898
Adj R-squared	0.799	0.815	0.919	0.755

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in parentheses. Sample is restricted to the 6-digit I-O benchmark industries during 1977–2014. Dependent variable is industry-level log of sales-weighted average markup estimated by Olley–Pakes method. $HIMP_{t-1}$ is one year lagged industry horizontal import penetration ratio. $VIMP_{t-1}$ is one year lagged industry vertical import penetration ratio. Specifications (1) and (2) report regressions across all sectors. Columns (3) and (4) report regression results for manufacturing and service sectors respectively. Other controls include the firm level of capital-labor ratio, TFP, sales, and industrial level of HHI. All variables are made log transformation. These results are robust to alternative specification of markup, i.e., the profit margin. The error terms are clustered at the industry level. Estimations are weighted by the firm number of the industry.

4.4. Resource reallocation to the high-markup firms

In the empirical results from the previous sections, VIMP shows a greater level of impact on the average markup when weighted by firms’ market shares, compared to the simple average. These results suggest that VIMP may lead to a market concentration to the high-markup firms. The market concentration toward the high-markup firms could contribute to the rise of the aggregate markup. Actually, Autor et al. (2020) and De Loecker et al. (2020) have attributed the rise of aggregate markup to the rise of superstar firms and market concentration. In this section, we continue to explore how the aggregate markup is adjusted through the resource-reallocation effect between high- and low-markup firms. We extend our main specification to the equation below to test this hypothesis:

Table 5
Sector-level COGS-weighted average markup.

Dependent variable	<i>lnMarkup</i>		Manufacturing	Services
	All sectors			
	(1)	(2)	(4)	(6)
<i>VIMP</i> _{<i>t</i>-1}	0.362*** (0.122)	0.364*** (0.119)	0.153* (0.090)	0.423*** (0.125)
<i>HIMP</i> _{<i>t</i>-1}	-0.018 (0.074)	-0.066 (0.071)	0.0006 (0.036)	0.856*** (0.179)
Other controls	NO	YES	YES	YES
Industry FEs	YES	YES	YES	YES
Year FEs	YES	YES	YES	YES
Observations	9771	9724	6826	2898
Adj R-squared	0.796	0.802	0.901	0.759

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in parentheses. Sample is restricted to the 6-digit I-O benchmark industries during 1977–2014. Dependent variable is industry-level log of COGS-weighted average markup estimated by Olley–Pakes method. *HIMP*_{*t*-1} is one year lagged industry horizontal import penetration ratio. *VIMP*_{*t*-1} is one year lagged industry vertical import penetration ratio. Specifications (1) and (2) report regressions across all sectors. Column (3) and (4) report regression results for manufacturing and service sectors respectively. Other controls include the firm level of capital-labor ratio, TFP, sales, and industrial level of HHI. All variables are made log transformation. These results are robust to alternative specification of markup, i.e., the profit margin. The error terms are clustered at the industry level. Estimations are weighted by the firm number of the industry.

Table 6
Sector-level simple average markup.

Dependent variable	<i>lnMarkup</i>		Manufacturing	Services
	All sectors			
	(1)	(2)	(4)	(6)
<i>VIMP</i> _{<i>t</i>-1}	0.225*** (0.081)	0.227*** (0.077)	0.155 (0.110)	0.233*** (0.079)
<i>HIMP</i> _{<i>t</i>-1}	-0.078 (0.056)	-0.059 (0.052)	0.007 (0.029)	0.507*** (0.172)
Other controls	NO	YES	YES	YES
Industry FEs	YES	YES	YES	YES
Year FEs	YES	YES	YES	YES
Observations	9771	9724	6826	2898
Adj R-squared	0.712	0.730	0.901	0.670

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in parentheses. Sample is restricted to the 6-digit I-O benchmark industries during 1977–2014. Dependent variable is industry-level log of simple average markup estimated by Olley–Pakes method. *HIMP*_{*t*-1} is one year lagged industry horizontal import penetration ratio. *VIMP*_{*t*-1} is one year lagged industry vertical import penetration ratio. Specifications (1) and (2) report regressions across all sectors. Columns (3) and (4) report regression results for manufacturing and service sectors respectively. Other controls include the firm level of capital-labor ratio, TFP, sales, and industrial level of HHI. All variables are made log transformation. These results are robust to alternative specification of markup, i.e., the profit margin. The error terms are clustered at the industry level. Estimations are weighted by the firm number of the industry.

$$\ln Sales_{ist} = \beta_1 HIMP_{st-1} + \beta_2 VIMP_{st-1} + \sum_k \beta_{3,k} Markup_rank_k \times VIMP_{st-1} + F_{it}^2 \gamma + \theta_i + \delta_t + \varepsilon_{st} \quad (20)$$

wherein $\ln Sales_{ist}$ is the log of sales for the firm i , who operates in industry s at year t in model (20).¹³ $Markup_rank_k$ is the indicator for the markup ranking in the initial year for the firm i , where firms are grouped in four intervals, that is, top 25% ($k = 1$), top 25–50% ($k = 2$), top 50–75% ($k = 3$), and bottom 25% ($k = 4$). F_{it} is added to account for time-variant firm-level factors including the capital-labor ratio, productivity, and industry’s HHI that could also influence a firm’s capacity of adjusting markups. We also include firm fixed-effects as captured by θ_i . Year fixed-effects are captured by δ_t .

The relevant results that reported in Table 8 confirm our theoretical hypothesis. Columns 1 and 2 of Table 8 show a significantly positive coefficients on the interaction between *VIMP* and the top 25% or top 25–50% group. These results suggest that with a higher imported inputs penetration ratio, the leading firms in terms of initial year’s markup increase more in market sales. The market shares concentrate toward the high-markup firms with exposure to a higher imported inputs penetration ratio. As a result, the sales-weighted average markup increases. For robust, we also use the COGS to measure the market concentration and replicate the estimation model (20). The results are consistent with the baseline estimations.

¹³ The results keep unchanged when using the total COGS as the dependent variable to measure the firm’s production scale.

Table 7
Firm-level adjustments on markup.

Dependent variable	<i>lnMarkup</i>		Manufacturing (3)	Services (4)
	All sectors (1)	(2)		
<i>VIMP</i> _{<i>t</i>-1}	0.054*** (0.015)	0.051*** (0.014)	0.054*** (0.016)	0.077** (0.036)
<i>HIMP</i> _{<i>t</i>-1}	-0.015*** (0.005)	-0.013** (0.005)	-0.015*** (0.005)	0.144 (0.099)
Other controls	NO	YES	YES	YES
Firm FEs	YES	YES	YES	YES
Year FEs	YES	YES	YES	YES
Observations	129,954	121,432	79,148	42,220
Adj R-squared	0.764	0.784	0.763	0.765

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in parentheses. Sample is restricted to the 6-digit I-O benchmark industries during 1977-2014. Dependent variable is firm-level log of markup estimated by Olley-Pakes Method. *HIMP*_{*t*-1} is one year lagged industry horizontal import penetration ratio. *VIMP*_{*t*-1} is one year lagged industry vertical import penetration ratio. Specifications (1) and (2) report regressions across all sectors. Columns (3) and (4) report regression results for manufacturing and service sectors respectively. Other controls include the firm level of capital-labor ratio, TFP, sales, and industrial level of HHI. All variables are made log transformation. Our baseline results are robust to alternative specification of markup, i.e., the profit margin. The error terms are clustered at the industry-year level.

4.5. Mechanism: global sourcing process and rise of leading firm

Our theoretical analysis predicts that the high-productivity firms are more likely to enter the outsourcing market and benefit more from the input-trade liberalization. Thus, the input globalization process will enhance these leading firms' market power as well as increasing their market shares. Meanwhile, our theoretical model also predicts a positive relation between a firm's productivity and its markup. Thus, such market concentration trend will finally lead to a market concentration toward the high-markup firms. Such resource-reallocation effect is supposed to be the main reason for the rise of aggregate markup. In this section, we will empirically test this theoretical hypothesis and uncover the transmission mechanism.

Using the firm-level data, we conduct the relevant empirical tests to confirm our theoretical predictions 1–3. The first test aims to confirm the positive correlation between the firms' productivity and performance. As mentioned above, the second test examines the increase in markup, profit rate, and sales by the leading firms (high-productivity firms), that is, the leading firms gain a higher markup and a greater share of the market. We do so by both extending our baseline specification and a DID exercise.

4.5.1. Patterns of leading firms

Our first theoretical prediction exhibits a better performance by high-productivity firms that revealed by higher markup, profit rate, and market sales.¹⁴ Here, we test this prediction by regressing each firm's markup on its TFP, while controlling for the firm level capital-labor ratio, firm fixed effects, and industry-year fixed effects. Table 9 reports the relevant results, which confirms the positive relation between firms' performance and their productivity.

4.5.2. Import penetration and markup changes among heterogeneous firms

Our theoretical model predicts that firms are motivated to employ more foreign inputs when variable sourcing cost decreases, but only the firms with relatively high productivity can use the foreign inputs and benefit from the input-trade liberalization. Thus, we expect that exposure to a higher importing penetration rate will benefit more to the high productivity firms. The high-productivity firms will enhance their market power, which is reflected by a biased rise in markup and market sales toward the high-productivity firms. To test this prediction, we categorize the firms into different groups based on their productivity rankings in each industry. We aim to distinguish the coefficient differences among different groups of firms, and expect a larger positive coefficient for the group with a higher productivity ranking. Specifically, the firms are recognized as within four groups according to their TFP rankings in the initial year in each industry (3-digit IO code), that is, top 25%, top 25–50%, top 50–75%, and bottom 25%. Then, we run the regressions with allowing the TFP ranking dummies on the *VIMP*. The dependent variables in the regressions are log of markup and log of sales (See the econometric model (21) below).

$$\ln Markup_{ist} = \beta_1 HIMP_{st-1} + \beta_2 VIMP_{st-1} + \sum_k \beta_{3,k} TFP_rank_k \times VIMP_{st-1} + F_{it}' \gamma + \theta_i + \delta_t + \varepsilon_{st} \quad (21)$$

wherein $\ln Markup_{ist}$ is the log of markup of the firm i , who operates in industry s at year t in model (21). TFP_rank_k is the indicator for the TFP ranking in the initial year for the firm i , where firms are grouped in four intervals, that is, top 25% ($k = 1$), top 25–50% ($k = 2$), top 50–75% ($k = 3$), and bottom 25% ($k = 4$). F_{it} is added to account for time-variant firm-level factors including the total sales, capital-

¹⁴ Due to the restriction on the data structure, we are unable to empirically test the relationship between firms' TFP and importing performance. Alternatively, we check this relationship using Chinese manufacturing data from 2000 to 2007. The estimation result shows that importing firms simultaneously pursue relatively high TFP.

Table 8
Market concentration toward high-markup firms.

Dependent variable	<i>lnSales</i>		Manufacturing (3)	Services (4)
	All sectors (1)	(2)		
$VIMP_{t-1}$	-0.418*** (0.095)	-0.238*** (0.082)	0.006 (0.092)	-0.109 (0.158)
$\times Top25\%$	0.995*** (0.111)	0.916*** (0.101)	0.642*** (0.114)	0.550** (0.249)
$\times Top25-50\%$	0.708*** (0.111)	0.421*** (0.101)	0.253** (0.121)	0.581** (0.291)
$\times Top50-75\%$	0.188* (0.101)	0.050 (0.096)	-0.091 (0.119)	-0.086 (0.170)
$HIMP_{t-1}$	-0.084*** (0.025)	-0.134*** (0.024)	-0.142*** (0.023)	0.854*** (0.167)
Other controls	NO	YES	YES	YES
Firm FEs	YES	YES	YES	YES
Year FEs	YES	YES	YES	YES
Observations	42,297	40,708	29,382	6973
Adj R-squared	0.931	0.946	0.955	0.931

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in parentheses. Sample is restricted to the 6-digit I-O benchmark industries during 1977–2014. Dependent variable is firm-level log of sales. $HIMP_{t-1}$ is the industry horizontal import penetration. $VIMP_{t-1}$ is the industry vertical import penetration ratio. Both variables are lagged one period in regressions. Top 25% is the dummy that equals to one if the firm is in the top 25% by TFP, and zero otherwise. Top 25–50% is the dummy that equals to one if the firm is between the top 25 and 50% by TFP, and zero otherwise. Top 50–75% is the dummy that equals to one if the firm is between the top 50 and 75% by TFP, and zero otherwise. Here, we rank the firms by their TFP in the initial year of the sample. Other controls include the firm level of capital-labor ratio, TFP, and industrial level of HHI. All variables are made log transformation. The error terms are clustered at the industry-year level. We also replicate the estimations with the COGS as the dependent variable. The results keep unchanged.

labor ratio, productivity, and industry's HHI that could also influence a firm's capacity of adjusting markups.¹⁵ We also include firm fixed-effects as captured by θ_i . Year fixed-effects are captured by δ_t .

Our empirical estimations show the consistent results with our theoretical predictions. Table 10 reports the relevant results. The estimations are based on three lengths of periods, the period covers our full sample, i.e., 1977 to 2014, period from 1977 to 1988, and the period from 1989 to 2014. Naturally, we use the firms' initial TFP in 1977 to identify firms' TFP ranking ranges for the regressions with both the periods 1977–2014 and 1977–1988, and the initial TFP in 1989 to identify firms' TFP ranking ranges for the regressions with the period 1989–2014. In the period 1989–2014, there was an economic openness process in a plenty of emerging countries that are supposed to be the major sourcing countries for United States now, such as Eastern European countries, China, India, and Vietnam. The estimations on the long period present the market-structure changes in the past four decades. While, the estimations on the second period focus on and emphasize the changes after the openness of Eastern Europe and China's entry into WTO. Based on the results reported in Table 10, we find that the coefficient is larger for the firms with higher TFP ranking for both periods, which indicates that the leading firms within each industry gain more market power in response to a higher input-import exposure rate.

4.5.3. Import penetration and market concentration to the high-productivity firms

In the preceding sector, we have shown that the rise of markup is mainly driven by the leading firms. In this section, we will further test the third theoretical prediction, i.e., market share will concentrate toward the leading firms. Such resource-reallocation effect is considered as the main causal factor that leads to the rise of sales-weighted average of markup. We specify the following estimation model to test this theoretical hypothesis.¹⁶

$$\ln Sales_{ist} = \beta_1 HIMP_{st-1} + \beta_2 VIMP_{st-1} + \sum_k \beta_{3,k} TFP_rank_k \times VIMP_{st-1} + F_{it}^i \gamma + \theta_i + \delta_t + \varepsilon_{st} \quad (22)$$

wherein $\ln Sales_{ist}$ is the log of total sales of the firm i , who operates in industry s at year t in model (22). TFP_rank_k is the indicator for the TFP ranking in the initial year for the firm i , where firms are grouped in four intervals, that is, top 25% ($k = 1$), top 25–50% ($k = 2$), top 50–75% ($k = 3$), and bottom 25% ($k = 4$). F_{it} is added to account for time-variant firm-level factors including the capital-labor ratio, productivity, and industry's HHI that could also influence a firm's capacity of adjusting markups. We also include firm fixed-effects as captured by θ_i . Year fixed-effects are captured by δ_t .

Table 11 reports the relevant results for concentration of market sales. Based on the results, we observe a higher positive effect of imported inputs penetration on sales received by the top 50% firms, while a negative effect on the bottom 25% firms, which suggests a crowding-out effect of input-trade liberalization on the lowest productivity firms and market share concentrates toward the leading firms. These results are consistent with our third theoretical prediction. Because the high-productivity firms are more likely to

¹⁵ The variable *sales* is not controlled when the dependent variable is *sales*.

¹⁶ The results keep unchanged when using the total COGS as the dependent variable to measure the firm's production scale.

Table 9
Mechanism: firms' productivity and performances.

Dependent variable	<i>lnMarkup</i>		<i>lnSales</i>		<i>lnProfits</i>	
	(1)	(2)	(3)	(4)	(5)	(6)
<i>TFP</i>	0.128*** (0.005)	0.131*** (0.005)	0.960*** (0.009)	0.972*** (0.001)	0.197*** (0.007)	0.203*** (0.007)
Other controls	NO	YES	NO	YES	NO	YES
Firm FEs	YES	YES	YES	YES	YES	YES
Industry-year FEs	YES	YES	YES	YES	YES	YES
Observations	135,204	135,204	135,204	135,204	127,291	127,291
Adj <i>R</i> -squared	0.764	0.764	0.941	0.999	0.710	0.715

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in parentheses. Sample is restricted to the 6-digit I-O benchmark industries during 1977–2014. *TFP* is the firm's total factors productivity that estimated by OP method. Other control variable is the firm level of log of capital-labor ratio. Columns (1) and (2) report the results for log of markup. Columns (3) and (4) report the results for log of sales. Columns of (5) and (6) report the result for log of profits. The error terms are clustered at the industry-year level.

simultaneously pursue high markups (Autor et al., 2020), a rise of market share by the high-productivity will lead to an increase in sales-weighted average of markup. We also replicate model (22) using the COGS as the dependent variable. The results are consistent with the baseline estimations.

Based on our theoretical model, the rise of market concentration is not only revealed by the reallocation of market sales toward the high-productivity firms, but also a rise in exit probability by the lowest-productivity firms (which is defined as the bottom 25% firms in our sample). We test this theoretical prediction by replace the dependent variable of model (22) with the exit dummy *Exit_Ratio_{ist}*, wherein *Exit_Ratio_{ist}* equals to one if the firm disappears from the sample in the next period, and zero otherwise. We perform the estimations with the Probit model for panel data analysis.

The relevant results are reported in Table 12. The results show a significantly positive coefficient on *VIMP*, while a significantly negative coefficient on the interaction between *VIMP* and top 75% firms. These results suggest a rise of exit probability for the bottom 25% firms, while such positive effect is much reduced for the top 75% firms. The results keep unchanged when performing with the linear probability model (LPM) while controlling the high-dimension fixed effects.

4.6. Changes of unit cost (cost per sale)

As discussed in the theoretical section, the increase in markup for each firm is dependent on a decrease in the firm's marginal cost. As the marginal cost is not directly observable, we explore this relationship by examining the connection between the firm's unit cost in production (variable cost) and *VIMP*. We calculate the unit cost as the ratio of direct COGS to sales, and if the marginal cost is monotonically increasing or constant to quantity, the firm's marginal cost will be linearly and positively correlated with its unit cost. To estimate this relationship, we extend our specification to the model (23) below.

Table 10
Mechanism: rise of market power by high-productivity firms.

Dependent variable	<i>lnMarkup</i>		1977–1988	1989–2014
	Full sample (1)	(2)	(3)	(4)
<i>VIMP_{t-1}</i>	-0.073*** (0.026)	-0.111*** (0.025)	-0.121*** (0.025)	-0.040 (0.025)
× <i>Top25%</i>	0.154*** (0.028)	0.223*** (0.028)	0.258*** (0.029)	0.149*** (0.028)
× <i>Top25-50%</i>	0.096*** (0.028)	0.130*** (0.026)	0.140*** (0.026)	0.046* (0.025)
× <i>Top50-75%</i>	0.091*** (0.030)	0.129*** (0.030)	0.154*** (0.030)	0.043* (0.025)
<i>HIMP_{t-1}</i>	-0.011 (0.006)	-0.009 (0.006)	-0.010 (0.006)	-0.024*** (0.006)
Other controls	NO	YES	YES	YES
Firm FEs	YES	YES	YES	YES
Year FEs	YES	YES	YES	YES
Observations	42,297	40,708	37,614	58,602
Adj <i>R</i> -squared	0.733	0.755	0.782	0.759

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in parentheses. Sample is restricted to the 6-digit I-O benchmark industries during 1977–2014. Dependent variable is firm-level log of markup estimated by Olley–Pakes Method. *HIMP_{t-1}* is the industry horizontal import penetration. *VIMP_{t-1}* is the industry vertical import penetration ratio. Both variables are lagged one period in regressions. Top 25% is the dummy that equals to one if the firm is in the top 25% by *TFP*, and zero otherwise. Top 25–50% is the dummy that equals to one if the firm is between the top 25 and 50% by *TFP*, and zero otherwise. Top 50–75% is the dummy that equals to one if the firm is between the top 50 and 75% by *TFP*, and zero otherwise. Here, we rank the firms by their *TFP* in the initial year of the sample. Other controls include the firm level of capital-labor ratio, sales, *TFP*, and industrial level of *HHI*. All variables are made log transformation. The error terms are clustered at the industry-year level.

$$\ln \text{Unit_cost}_{ist} = \beta_1 \text{HIMP}_{st-1} + \beta_2 \text{VIMP}_{st-1} + \sum_k \beta_{3,k} \text{TFP_rank}_k \times \text{VIMP}_{st-1} + F_{it}' \gamma + \theta_i + \delta_t + \varepsilon_{st} \quad (23)$$

where $\ln \text{Unit_cost}_{ist}$ is the log of ratio of direct COGS to sales of the firm i , who incurs in industry s at year t in model (24). TFP_rank_k is the indicator for the TFP ranking in the initial year for the firm i , where firms are grouped in four intervals, that is, top 25% ($k = 1$), top 25–50% ($k = 2$), top 50–75% ($k = 3$), and bottom 25% ($k = 4$). F_{it} is added to account for time-variant firm-level factors including the capital-labor ratio, productivity, and industry's HHI that could also influence a firm's capacity of adjusting markups. We also include firm fixed-effects as captured by θ_i . Year fixed-effects are captured by δ_t .

Table A1 (see the table in Appendix) presents the pertinent findings of our analysis. The results demonstrate that VIMP has a negative impact on firms' unit costs, with more productivity firms experiencing a greater reduction in unit costs. These findings lend support to our hypothesis that firms respond to an increased importation of inputs by reducing their marginal costs.

4.7. Alternative indicator for markup (profit margin)

In the preceding section, we employed the markup index put forward by Autor et al. (2020) to assess the impact of VIMP on markup. To ensure the robustness of our results, we conducted a replication of the estimation model (21) using the profit margin to sales ratio, which measures the relationship between firm-level profits and sales. Our baseline estimates were corroborated by the results presented in Table A2 (see the table in Appendix), indicating that dominant firms experienced a more substantial increase in profit rates. This suggests that leading firms have been able to augment their market power. To rule out the possibility that the profit margin results were influenced by changes in firms' sales, we examined the total profit changes of heterogeneous firms, and the relevant results are reported in Table A3 (see the table in Appendix). These results reveal that dominant firms experienced a higher increase in total profits, implying that they have been able to achieve greater profitability.

4.8. A difference-in-difference exercise: the import shock from China's PNTR status

We replicate the relevant estimations by applying the DID exercise to the sample from 1989 to 2007 to ensure the robustness of the empirical results. At the end of 2001, the United States granted China Permanent Normal Trade Relations (PNTR) in response to China's entry into the World Trade Organization (WTO). Consequently, the change in U.S. trade policy has removed the possibility of tariff increases on Chinese imports, thereby significantly reducing policy uncertainty on Chinese products. It may affect the anticipated profitability of importing and, as a result, influence the magnitude of trade flows that are driven by offshoring and outsourcing. Accordingly, industries more exposed to the change are experiencing substantial increases in imports from China and increased entry from US importers and foreign-owned Chinese exporters (Handley and Limão, 2017; Pierce and Schott, 2016). Here we take advantage of the sudden removal of trade uncertainty, which generates cross-industry variations, and apply a similar identification strategy to Pierce and Schott (2016) to analyze the impact of increased imports on markups both directly and indirectly through their supply chains. In this way, we can minimize the measurement and endogeneity considerations that may arise from import penetration measures as described in the previous sections.

Specifically, we leverage the gap between the NTR tariffs and the non-NTR tariffs as a proxy for HIMP, and derive upstream NTR gap the same way as deriving VIMP. The industry-level data for NTR gaps are constructed by Pierce and Schott (2016) as the difference of ad valorem tariffs between NTR and non-NTR status. The upstream NTR gap is constructed by the same approach as measuring VIMP in Section 3:

$$\text{NTR_GAP}_{st}^{up} = \sum_{j \in s} d_{js} \tau_{jt} \quad (24)$$

where the upstream NTR gap of industry s , NTR_GAP_{st}^{up} , is calculated as the weighted average of the NTR gaps NTR_GAP_{jt} in any industry j whose product has been used as input to produce output in industry s at time t . Similar to the measure of VIMP, d_{js} remains the use value shares of industry j to the production of industry s as in Section 3. We follow Pierce and Schott (2016) in using the NTR gaps in 1999 and the use value shares are concorded using the concordance table between I-O table and SIC provided in the 1997 benchmark I-O table.

Next, we can exploit this specific exogenous policy that changes import penetration to address the potential issue of endogeneity. We adopt a Difference-in-Difference approach based on the China's accession of permanent NTR status, which eliminated the tariff uncertainty and greatly spurred import of Chinese goods in the US market. Many researchers have considered this 'China Shock' and have examined its impacts on the US economy in various aspects (Dorn et al., 2018; Acemoglu et al., 2016; Autor et al., 2018; Autor et al., 2016). We consider a sample of manufacturing import penetration from China between 1989 and 2006 and begin with a specification in the spirit of Guadalupe and Wulf (2010) as follows,

$$\ln \text{Markup}_{ist} = \beta_1 \text{NTR_GAP}_{s,1999} \times \text{POST} + \beta_2 \text{NTR_GAP}_{s,1999}^{up} \times \text{POST} + \sum_k \beta_{3,k} \text{TFP_rank}_k \times \text{NTR_GAP}_{s,1999}^{up} \times \text{POST} + X_{ist}' \Gamma + \sigma_i + \theta_s + \delta_t + \varepsilon_{ist} \quad (25)$$

where $\text{NTR_GAP}_{s,1999}$ and $\text{NTR_GAP}_{s,1999}^{up}$ are the own and upstream NTR gaps for industry s respectively in 1999. These measures are interacted with post dummy, POST , a dummy variable equal to 1 in each year after 2001. TFP_rank_k is the indicator for the TFP ranking

Table 11
Mechanism: market concentration toward high-productivity firms.

Dependent variable	<i>lnSales</i>		1977–1988 (3)	1989–2014 (4)
	Full sample (1)	(2)		
$VIMP_{t-1}$	-0.179* (0.101)	-0.225** (0.099)	-0.295*** (0.106)	-0.481*** (0.081)
$\times Top25\%$	0.409*** (0.118)	0.709*** (0.115)	0.934*** (0.122)	0.712*** (0.098)
$\times Top25-50\%$	0.339*** (0.119)	0.417*** (0.113)	0.444*** (0.117)	0.805*** (0.103)
$\times Top50-75\%$	0.160 (0.111)	0.050 (0.108)	0.037 (0.115)	0.712*** (0.094)
$H IMP_{t-1}$	-0.083*** (0.025)	-0.129*** (0.024)	-0.139*** (0.024)	-0.042** (0.021)
Other controls	NO	YES	YES	YES
Firm FEs	YES	YES	YES	YES
Year FEs	YES	YES	YES	YES
Observations	42,297	40,708	37,614	58,602
Adj R-squared	0.931	0.946	0.951	0.943

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in parentheses. Sample is restricted to the 6-digit I-O benchmark industries during 1977–2014. Dependent variable is firm-level log of sales. $HIMP_{t-1}$ is the industry horizontal import penetration and $VIMP_{t-1}$ is the industry vertical import penetration ratio. Both variables are lagged one period in regressions. Top 25% is the dummy that equals to one if the firm is in the top 25% by TFP, and zero otherwise. Top 25–50% is the dummy that equals to one if the firm is between the top 25 and 50% by TFP, and zero otherwise. Top 50–75% is the dummy that equals to one if the firm is between the top 50 and 75% by TFP, and zero otherwise. Here, we rank the firms by their TFP in the initial year of the sample. Other controls include the firm level of capital-labor ratio, TFP, and industrial level of HHI. All variables are made log transformation. The error terms are clustered at the industry-year level. We also replicate the estimations with the COGS as the dependent variable. The results keep unchanged.

Table 12
Mechanism: exit of lowest-productivity firms.

Dependent variable	<i>Exit dum</i>		1977–1988 (3)	1989–2014 (4)
	Full sample (1)	(2)		
$VIMP_{t-1}$	0.924*** (0.144)	0.873*** (0.155)	1.010*** (0.166)	0.726*** (0.103)
$\times Top25\%$	-0.404** (0.161)	-0.450*** (0.174)	-0.484*** (0.185)	-0.538*** (0.118)
$\times Top25-50\%$	-0.480*** (0.176)	-0.444** (0.187)	-0.416** (0.197)	-0.601*** (0.127)
$\times Top50-75\%$	-0.152 (0.170)	-0.156 (0.181)	-0.138 (0.191)	-0.399*** (0.122)
$H IMP_{t-1}$	0.216*** (0.053)	0.165*** (0.056)	0.188*** (0.058)	0.141*** (0.039)
Other controls	NO	YES	YES	YES
Random effects	YES	YES	YES	YES
Observations	40,198	38,509	35,980	56,022
Wald chi2	120.26	290.01	320.19	289.12
Prob>chi2	0.000	0.000	0.000	0.000

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in parentheses. Sample is restricted to the 6-digit I-O benchmark industries during 1977–2014. Dependent variable is firm-level exit dummy. We use the Probit model for panel data analysis to perform the estimations. The results keep unchanged when performing with the linear probability model (LPM) with controlling the firm and year fixed effects and clustering at the industry-year level. Sample is restricted to the 6-digit I-O benchmark industries during 1977–2014. Dependent variable is exit ratio. $HIMP_{t-1}$ is the industry horizontal import penetration and $VIMP_{t-1}$ is the industry vertical import penetration ratio. Both variables are lagged one period in regressions. Top 25% is the dummy that equals to one if the firm is in the top 25% by TFP, and zero otherwise. Top 25–50% is the dummy that equals to one if the firm is between the top 25 and 50% by TFP, and zero otherwise. Top 50–75% is the dummy that equals to one if the firm is between the top 50 and 75% by TFP, and zero otherwise. Here, we rank the firms by their TFP in the initial year of the sample. Other controls include the firm level of capital-labor ratio, sales, TFP, and industrial level of HHI. All variables are made log transformation. The error terms are clustered at the industry-year level.

in the initial year for the firm i , where firms are grouped in four intervals, that is, top 25% ($k = 1$), top 25–50% ($k = 2$), top 50–75% ($k = 3$), and bottom 25% ($k = 4$). And X_{ist} is a matrix of firm- and industry-level control variables to controls for firm and industrial characteristics, including NTR tariff rates, union membership rates, the log of capital and skill intensity in the first year the plant is observed, contract intensity (Nunn, 2007), changes in Chinese import tariffs, changes in Chinese production subsidies, an indicator for whether the industry produces advanced technology products, firm-level TFP, sales, and the endogeneity of import penetration

Table A1
Mechanism: reduction in unit cost (cost per sale).

Dependent variable	<i>lnUnit_cost</i>			1977–1988 (4)	1989–2014 (5)
	(1)	Full sample (2)	(3)		
$VIMP_{t-1}$	-0.054*** (0.015)	-0.051*** (0.014)	-0.018* (0.010)	0.048 (0.053)	0.191** (0.086)
× <i>Top25%</i>			-0.027* (0.014)	-0.262*** (0.057)	-0.304*** (0.103)
× <i>Top25-50%</i>			-0.018 (0.011)	-0.166*** (0.055)	-0.200*** (0.064)
× <i>Top50-75%</i>			0.001 (0.013)	0.023 (0.055)	-0.244*** (0.066)
$HIMP_{t-1}$	0.015*** (0.005)	0.013** (0.005)	-0.053** (0.024)	0.043*** (0.015)	0.084*** (0.025)
Other controls	NO	YES	YES	YES	YES
Firm FEs	YES	YES	YES	YES	YES
Year FEs	YES	YES	YES	YES	YES
Observations	129,954	121,432	47,373	33,451	53,455

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in parentheses. Sample is restricted to the 6-digit I-O benchmark industries during 1977–2014. Dependent variable is firm-level unit cost, which is computed as the ratio of COGS to sale. $HIMP_{t-1}$ is the industry horizontal import penetration. $VIMP_{t-1}$ is the industry vertical import penetration ratio. Both variables are lagged one period in regressions. Top 25% is the dummy that Top 25% is the dummy that equals to one if the firm is in the top 25% by TFP, and zero otherwise. Top 25–50% is the dummy that equals to one if the firm is between the top 25 and 50% by TFP, and zero otherwise. Top 50–75% is the dummy that equals to one if the firm is between the top 50 and 75% by TFP, and zero otherwise. Here, we rank the firms by their TFP in the initial year of the sample. Other controls include the firm level of capital-labor ratio, sales, TFP, and industrial level of HHI. All variables are made log transformation. The error terms are clustered at the industry-year level.

Table A2
Alternative indicator for market power: profit margin.

Dependent variable	<i>lnProfit_margin</i>			1977–1988 (4)	1989–2014 (5)
	(1)	Full sample (2)	(3)		
$VIMP_{t-1}$	0.105*** (0.032)	0.115*** (0.031)	0.046 (0.082)	0.020 (0.088)	0.034 (0.066)
× <i>Top25%</i>			0.203** (0.081)	0.231*** (0.087)	0.236*** (0.072)
× <i>Top25-50%</i>			0.121 (0.081)	0.163* (0.085)	0.140** (0.071)
× <i>Top50-75%</i>			0.097 (0.088)	0.127 (0.093)	-0.0004 (0.071)
$HIMP_{t-1}$	-0.013 (0.013)	-0.001 (0.012)	0.004 (0.017)	-0.012 (0.018)	-0.016 (0.014)
Other controls	NO	YES	YES	YES	YES
Firm FEs	YES	YES	YES	YES	YES
Year FEs	YES	YES	YES	YES	YES
Observations	122,217	114,893	38,857	35,968	55,903
Adj R-squared	0.687	0.707	0.665	0.680	0.687

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in parentheses. Sample is restricted to the 6-digit I-O benchmark industries during 1977–2014. Dependent variable is firm-level ratio of profit to sale. $HIMP_{t-1}$ is the industry horizontal import penetration. $VIMP_{t-1}$ is the industry vertical import penetration ratio. Both variables are lagged one period in regressions. Top 25% is the dummy that equals to one if the firm is in the top 25% by TFP, and zero otherwise. Top 25–50% is the dummy that equals to one if the firm is between the top 25 and 50% by TFP, and zero otherwise. Top 50–75% is the dummy that equals to one if the firm is between the top 50 and 75% by TFP, and zero otherwise. Here, we rank the firms by their TFP in the initial year of the sample. Other controls include the firm level of capital-labor ratio, sales, TFP, and industrial level of HHI. All variables are made log transformation. The error terms are clustered at the industry-year level.

through a set of time and firm fixed effects. Identification in the model thus comes from comparing the average NTR gaps of each industry that has different levels of initial own and upstream NTR gaps before China was granted PNTR in 2001. We are interested in the question that if industries with relatively high levels in initial trade uncertainties changed markup differently after 2001 more than industries facing low initial levels of trade uncertainties. We thus expect β_2 to be positive as industries who have greater upstream trade uncertainty reduction will be able to raise average markups with increased imported input penetration from China.

Table A4 (see the table in Appendix) reports the results of the effect of PNTR and the impacts on markups and sales by heterogeneous firms. Based on the columns (1) and (2), the positive coefficient of $NTR_GAP_{s,1999}^{HP} \times POST$ indicates that industries with lower vertical import penetration levels prior to 2001 increase markup over the period as they have improved access to input and concentrated market structure due to China's PNTR status after 2001. The results from heterogeneous regressions are reported in

Table A3
Mechanism: concentration of profits towards high-productivity firms.

Dependent variable	<i>lnProfits</i>				
	(1)	Full sample (2)	(3)	1977–1988 (4)	1989–2014 (5)
$VIMP_{t-1}$	0.201*** (0.063)	0.115*** (0.031)	-0.147 (0.129)	-0.217 (0.141)	0.034 (0.066)
× <i>Top25%</i>			0.913*** (0.147)	1.177*** (0.158)	0.236*** (0.072)
× <i>Top25-50%</i>			0.553*** (0.144)	0.624*** (0.153)	0.140** (0.071)
× <i>Top50-75%</i>			0.121 (0.136)	0.126 (0.146)	-0.0004 (0.071)
$HIMP_{t-1}$	-0.085*** (0.026)	-0.001 (0.012)	-0.123*** (0.029)	-0.147*** (0.030)	-0.016 (0.014)
Other controls	NO	YES	YES	YES	YES
Firm FEs	YES	YES	YES	YES	YES
Year FEs	YES	YES	YES	YES	YES
Observations	122,217	114,893	38,857	35,968	55,903
Adj <i>R</i> -squared	0.881	0.964	0.911	0.916	0.967

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in parentheses. Sample is restricted to the 6-digit I-O benchmark industries during 1977–2014. Dependent variable is firm-level log of total profits. $HIMP_{t-1}$ is the industry horizontal import penetration. $VIMP_{t-1}$ is the industry vertical import penetration ratio. Both variables are lagged one period in regressions. Top 25% is the dummy that equals to one if the firm is in the top 25% by TFP, and zero otherwise. Top 25–50% is the dummy that equals to one if the firm is between the top 25 and 50% by TFP, and zero otherwise. Top 50–75% is the dummy that equals to one if the firm is between the top 50–75% by TFP, and zero otherwise. Here, we rank the firms by their TFP in the initial year of the sample. Other controls include the firm level of capital-labor ratio, sales, TFP, and industrial level of HHI. All variables are made log transformation. The error terms are clustered at the industry-year level.

columns (3)–(6), we observe that high upstream NTR gaps are positively associated with firms’ markup and sales, while high-productivity firms increase more in both indicators. These results are consistent with our theoretical prediction that input-trade liberalization leads to the rise of leading firms.

5. Conclusion

From 1960 to 2014, the value of imports to GDP in the United States increased significantly, rising from 4.2% to around 16.5%. In

Table A4
Difference-in-difference exercise: the import shock from China’s PNTR status.

Dependent variable	<i>lnMarkup</i>			<i>lnSales</i>		
	(1)	(2)	(3)	(4)	(5)	(6)
$NTR_GAP^{IP} \times POST$	1.896*** (0.353)	1.202*** (0.284)	1.378*** (0.440)	0.135 (0.368)	4.149*** (1.080)	0.946 (0.715)
× <i>Top25%</i>			0.630** (0.255)	0.857*** (0.268)	2.310*** (0.488)	2.767*** (0.392)
× <i>Top50-25%</i>			0.274 (0.252)	0.605** (0.248)	0.285 (0.523)	1.310*** (0.468)
× <i>Top75-50%</i>			0.138 (0.259)	0.526** (0.261)	-0.270 (0.574)	0.793* (0.469)
$NTR_GAP \times POST$	0.077* (0.046)	0.074* (0.044)	0.052 (0.045)	0.132*** (0.045)	-0.126 (0.166)	0.171 (0.105)
Other controls	NO	YES	NO	YES	NO	YES
Firm FEs	YES	YES	YES	YES	YES	YES
Year FEs	YES	YES	YES	YES	YES	YES
Observations	38,381	36,056	36,660	31,205	36,660	31,205
Adj <i>R</i> -squared	0.744	0.758	0.746	0.791	0.932	0.960

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Table reports results of industry-year level OLS generalized difference-in-differences regressions of either log of markup or log of sales on the interaction of a post-PNTR indicator and the own and downstream NTR gaps. Additional controls include NTR tariff rates, union membership rates, capital and skill intensity in the first year the plant is observed, contract intensity (Nunn, 2007), changes in Chinese import tariffs, changes in Chinese production subsidies, an indicator for whether the industry produces advanced technology products, firm-level TFP, sales (for Columns (1)–(4)), and the endogeneity of import penetration through a set of time and industry fixed effects. All variables take log. Top 25% is the dummy that equals to one if the firm is in the top 25% by TFP, and zero otherwise. Top25–50% is the dummy that equals to one if the firm is between the top 25 and 50% by TFP, and zero otherwise. Top 50–75% is the dummy that equals to one if the firm is between the top 50–75% by TFP, and zero otherwise. Here, we rank the firms by their TFP in 1989. Data span 1989 to 2007. Robust standard errors adjusted for clustering at the level of the plants’ major industries and time are displayed below each coefficient. Estimates for the year (t) and industry (i) fixed effects as well as the constant are suppressed. We also replicate the estimations with the COGS as the dependent variable. The results keep unchanged.

almost the same period, from the late 1970s to 2014, we observe a rising trend in market concentration and aggregate markup in the U. S.. This suggests a potentially parallel growth trend between the imported input penetration, resource reallocation, and market structure changes. Existing research has focused on the effects of imports on firm strategies following the removal of trade barriers during specific periods. However, it remains unclear how the increasing trend in imports contributes to the reallocation of industrial resources and subsequent increase in aggregate markup.

The first objective of our study is to investigate the reasons behind the increasing trend in markup in the United States, and whether globalization can offer an explanation, either in part or entirely. The second objective is to analyze the potential impact of input globalization, which may lead to cost savings but also intensify competition in upstream markets. The net aggregate effect of input globalization is uncertain and requires further investigation. Our analysis of different sectors indicates that overall, input import penetration has a positive impact on markups, with the competition effect being in small scale or insignificant. For example, our findings with the firm-level estimations suggest that the scale of elasticity of vertical input import penetration (VIMP) is significantly higher than that of horizontal input import penetration (HIMP), which implies that imports, in general, promote markups. In our theoretical analysis, we demonstrate that when the same domestic firm produces both the intermediate inputs and final goods, the net markup effect of VIMP will be positive. When the domestic input users do not produce inputs themselves, the scale of competition effect on domestic input producers depends on the relative scale of complementary and substitution effect. If the complementary effect between production factors is greater than their substitution effect, an increase in sales scale resulting from the reduction in production costs will stimulate the downstream firms to increase demand for domestic intermediate inputs, or at least not to reduce the usage of domestic inputs.

Our paper adds to the existing literature by examining the heterogeneous responses of firms to the reduction of trade costs and the rise of global sourcing, and the resulting changes in market structure and firms' market power. We develop a theoretical framework that explains how increased penetration of input imports leads to higher average markups and reallocation of resources to the leading firms. We then provide empirical evidence to test the predictions made by our theory. Our research contributes to the literature in two ways. First, we consider the structural impact of the globalization process on industries over the past four decades, including the short-term effects of trade cost reduction on firms' markups and the long-term effects on resource allocation and market structure, emphasizing the rise of superstar firms induced by globalization. Secondly, we propose a theoretical framework for identifying and decomposing the effects of input-trade liberalization, which provides a solid basis for structural analysis and understanding the trade-related gains and losses. Most studies in the existing literature conclude that trade liberalization leads to an increase in the import of output goods, which has precompetition effects and reduces the inequalities of markup distribution, as demonstrated by Edmond et al. (2015). However, our study adds to the theoretical literature by exploring the rise in the penetration of imported inputs, mainly driven by the outsourcing of production processes overseas and the decline of trade costs. Along with the depth of penetration of imported inputs, we find that market power is enhanced for the leading firm, thereby reducing the efficiency of the allocation of resources.

Although our paper does not analyze firms' decisions regarding outsourcing to contract firms or offshoring under imperfect information, nor does it distinguish and analyze the behavior of importers from non-importers in depth due to inadequate data, we believe that further research should focus on quantifying the combined effects of these factors on markups. By better understanding how these factors interact, we can gain a more complete map on the impact of globalization on market structure and resource allocation.

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Appendix

Tables A1–A4

1. Proof of Lemma 1

Lemma 1 is equivalent to the following claims: φ_m is the unique solution to the equation $H(\varphi_m) \equiv \frac{[2\varphi_d - (V^{\phi} + 1)\varphi_m](1 - V^{\phi})\varphi_m \bar{D}^2}{4\gamma} - f_m = 0$ in the definition range $\varphi \in [\underline{\varphi}, +\infty)$; $H(\varphi_i) > 0$ for $\varphi_i < \varphi_m$; and $H(\varphi_i) < 0$ for $\varphi_i > \varphi_m$.

The solutions to the equation $H(\varphi_m) = 0$ in the definition range $\varphi_m \in \mathbb{R}$ are: $\varphi_{m1} = \frac{\varphi_d - \sqrt{\varphi_d^2 - \frac{4\gamma f_m(1+\Psi)}{L(1-\Psi)}}}{1+\Psi}$ or $\varphi_{m2} = \frac{\varphi_d + \sqrt{\varphi_d^2 - \frac{4\gamma f_m(1+\Psi)}{L(1-\Psi)}}}{1+\Psi}$. As $\varphi > 2\sqrt{\frac{\gamma f_m(1+\Psi)}{L(1-\Psi)}}$, the real-value solutions for φ_{m1} and φ_{m2} can be reached. Moreover, when $\varphi < \varphi_{m1}$ or $\varphi > \varphi_{m2}$, then $H(\varphi) < 0$; when

$\varphi_{m2} \geq \varphi \geq \varphi_{m1}$, then $H(\varphi) \geq 0$. As $\varphi \in [\underline{\varphi}, +\infty)$ and $\frac{\varphi_d - \sqrt{\varphi_d^2 - \frac{4\varphi_m(1+\Psi)}{L(1-\Psi)}}}{1+\Psi}$ decreases in φ_d , we have $\underline{\varphi} > \frac{\varphi_d - \sqrt{\varphi_d^2 - \frac{4\varphi_m(1+\Psi)}{L(1-\Psi)}}}{1+\Psi} \geq \frac{\varphi - \sqrt{\varphi^2 - \frac{4\varphi_m(1+\Psi)}{L(1-\Psi)}}}{1+\Psi}$. Thus,

we have the unique solution for the importing critic value in the definition range $\varphi \in [\underline{\varphi}, +\infty)$: (i) $\varphi_m = \frac{\varphi_d + \sqrt{\varphi_d^2 - \frac{4\varphi_m(1+\Psi)}{L(1-\Psi)}}}{1+\Psi}$ if

$$\varphi_d \geq \frac{\varphi_d + \sqrt{\varphi_d^2 - \frac{4\varphi_m(1+\Psi)}{L(1-\Psi)}}}{1+\Psi} \geq \varphi; \text{ (ii) } \varphi_m < \varphi \text{ if } \varphi > \frac{\varphi_d + \sqrt{\varphi_d^2 - \frac{4\varphi_m(1+\Psi)}{L(1-\Psi)}}}{1+\Psi}; \text{ and (iii) } \varphi_m > \varphi_d \text{ if } \varphi_d < \frac{\varphi_d + \sqrt{\varphi_d^2 - \frac{4\varphi_m(1+\Psi)}{L(1-\Psi)}}}{1+\Psi}.$$

Solution (i) is an interior solution, where some firms import intermediate inputs, and some firms use the domestic inputs. Solution (ii) and (iii) are corner solutions. Solution (i) indicates that all firms use the domestic inputs only. Solution (iii) indicates that all firms import the foreign inputs.

Q.E.D.

2. Math steps for estimation of markup

The estimation of markup follows the same method as in [De Loecker et al. \(2016\)](#). Here we sketch out the basic ideas. Using the methodology in [De Loecker and Warzynski \(2012\)](#), no inference from demand or market structure. Starting with a production technology

$$Q_{it}(V_{it}; K_{it}; \Omega_{it}) = F_{it}(V_{it}; K_{it})\Omega_{it} \tag{A1}$$

The associated Lagrangian function (with one composite input) is:

$$L(V_{it}; K_{it}; \Omega_{it}) = P_{it}^V V_{it} + r_{it} K_{it} - \lambda_{it}(Q_{it}(\cdot) - Q_{it}) \tag{A2}$$

First-Order Condition with respect to the variable input V gives

$$\frac{\partial Q_{it}(\cdot)}{\partial V_{it}} \frac{V_{it}}{Q_{it}} \equiv \theta_{it}^V = \frac{1}{\lambda_{it}} \frac{P_{it}^V V_{it}}{Q_{it}} \tag{A3}$$

wherein θ_{it}^V is the output elasticity of the variable input V_{it} and the Lagrangian multiplier λ_{it} is a measure of marginal cost. Rearranging the terms we have markup μ_{it} defined as price over marginal cost

$$\mu_{it} \equiv \frac{P_{it}}{\lambda_{it}} = \theta_{it}^V \frac{P_{it} Q_{it}}{P_{it}^V V_{it}} \tag{A4}$$

where the output elasticity θ_{it}^V is estimated from production function estimation and $\frac{P_{it} Q_{it}}{P_{it}^V V_{it}}$ is the inverse of input revenue share of the variable input V_{it} , which could be directly calculated from firm-level accounting data.

3. Math steps on the case of domestic sourcing

We start the proof from the formula of composite inputs and the associated demand function for inputs computed from this index.

$$X_i = \left(D_i^{\frac{\xi}{1+\xi}} + aM_i^{\frac{\xi}{1+\xi}} \right)^{\frac{1+\xi}{\xi}} \tag{A5}$$

\Rightarrow

$$L(\cdot) = \max_{\{D_i, M_i\}} \left(D_i^{\frac{\xi}{1+\xi}} + aM_i^{\frac{\xi}{1+\xi}} \right)^{\frac{1+\xi}{\xi}} + \lambda(c_i - p_D D_i - p_M M_i) \tag{A6}$$

\Rightarrow

$$\left(D_i^{\frac{\xi}{1+\xi}} + aM_i^{\frac{\xi}{1+\xi}} \right)^{\frac{1+\xi}{\xi}} D_i^{-\frac{1}{1+\xi}} - \lambda p_D = 0 \tag{A7}$$

$$\left(D_i^{\frac{\xi}{1+\xi}} + aM_i^{\frac{\xi}{1+\xi}} \right)^{\frac{1+\xi}{\xi}} aM_i^{-\frac{1}{1+\xi}} - \lambda p_M = 0 \tag{A8}$$

\Rightarrow

Then we get the relative demand function for domestic inputs.

$$\frac{D_i}{M_i} = \left(\frac{p_M}{ap_D} \right)^{1+\xi} \tag{A9}$$

\Rightarrow

$$\frac{D_i}{X_i} = \left[1 + \left(\frac{ap_D}{p_M} \right)^\xi \right]^{-\frac{1+\xi}{\xi}} \tag{A10}$$

\Rightarrow

Linearizing the relative demand function, we get:

$$\ln D_i = \ln \left(\frac{D_i}{X_i} \right) + \ln X_i \quad (\text{A11})$$

⇒

$$\frac{d \ln D_i}{d \ln p_M} = \frac{d \ln(D_i/X_i)}{d \ln p_M} + \frac{d \ln X_i}{d \ln p_M} \quad (\text{A12})$$

(1) (2)

⇒

$$\left\{ \begin{array}{l} \frac{d \ln(D_i/X_i)}{d \ln p_M} = \frac{(1 + \xi) \left(\frac{ap_D}{p_M} \right)^\xi}{1 + \left(\frac{ap_D}{p_M} \right)^\xi} < 1 + \xi \\ \frac{d \ln X_i}{d \ln p_M} = \frac{d \ln X_i}{d \ln V_i} \cdot \frac{d \ln V_i}{d \ln p_M} \end{array} \right. \quad (\text{A13})$$

Assume $p_i = -ky_i + z$, wherein $k \equiv \frac{z}{y_i}$

$$\begin{aligned} \frac{d \ln X_i}{d \ln V_i} &= \frac{\Phi X_i^{-1} p_i - k}{\Phi(\Phi - 1)X_i^{-1} p_i - 2\Phi k} \\ &= \frac{1 - k\Phi^{-1}X_i p_i^{-1}}{\Phi - 1 - 2kX_i p_i^{-1}} \end{aligned} \quad (\text{A14})$$

For simplicity without of losses of generality, we assume the intermediate input price equals to wage rate, i.e., $V_i = w$, then we have:

$$\frac{d \ln X_i}{d \ln V_i} = -\frac{1 - E_i^{-1}}{1 - \Phi + 2\Phi E_i^{-1}} \quad (\text{A15})$$

wherein $E_i \equiv \left| \frac{\partial y_i}{\partial p_i} \frac{p_i}{y_i} \right| > 0$ is absolute value of the demand elasticity for good i . Furthermore, we assume the price of domestic input is more expensive than the imported input when accounting the high technology embodied in the imported input, i.e., $p_D \geq \frac{p_M}{\alpha}$.

$$\frac{d \ln V_i}{d \ln p_M} = \left[\left(\frac{ap_D}{p_M} \right)^{-\epsilon} + 1 \right]^{-1} > \frac{1}{2} \quad (\text{A16})$$

Then we have:

$$\begin{aligned} \frac{d \ln D_i}{d \ln p_M} &= \frac{d \ln(D_i/X_i)}{d \ln p_M} + \frac{d \ln X_i}{d \ln p_M} \\ &= \frac{d \ln(D_i/X_i)}{d \ln p_M} + \frac{d \ln X_i}{d \ln V_i} \cdot \frac{d \ln V_i}{d \ln p_M} \\ &< 1 + \xi - \frac{1}{2} \cdot \frac{1 - E_i^{-1}}{1 - \Phi + 2\Phi E_i^{-1}} \end{aligned} \quad (\text{A17})$$

When substitution ratio between foreign and domestic inputs ξ is small enough, while the value for technological parameter of intermediate input Φ and absolute value for demand elasticity E_i are large enough, we have:

$$\frac{d \ln D_i}{d \ln p_M} < 1 + \xi - \frac{1}{2} \cdot \frac{1 - E_i^{-1}}{1 - \Phi + 2\Phi E_i^{-1}} \leq 0 \quad (\text{A18})$$

Then, a reduction in imported input price has negative or mute effects on the demand for domestic inputs. In this case, as the demand increases, the price and markup of domestic inputs will not decrease. A small value for ξ insures a small substitution effect between the two types of inputs. A large value for Φ and E_i guarantees that the production scale is large enough to drive up the demand for domestic inputs, or at least not depressing the demand. Though the demand and price for domestic inputs do not decline given the settings above, the relative sales share of the domestic inputs to the downstream firms that use the inputs will decline.

Next, we will show how the aggregate markup $\overline{\text{Markup}}_{\text{Agg}}$ changes given the presumption that the markup for domestic inputs doesn't change, i.e., $\Delta \overline{\text{Markup}}_{\text{input}} = 0$, but the market share of the domestic firms that produce the inputs declines due to the scale expansion of downstream importing firms.

$$\begin{aligned}
\Delta \overline{\text{Markup}}_{\text{Agg}} &= (S_{\text{input}} - \Delta S) (\overline{\text{Markup}}_{\text{input}} + \Delta \overline{\text{Markup}}_{\text{input}}) \\
&+ (S_{\text{user}} + \Delta S) (\overline{\text{Markup}}_{\text{user}} + \Delta \overline{\text{Markup}}_{\text{user}}) - S_{\text{input}} \overline{\text{Markup}}_{\text{input}} - S_{\text{user}} \overline{\text{Markup}}_{\text{user}} \\
&= -\Delta S \overline{\text{Markup}}_{\text{input}} + \Delta S \overline{\text{Markup}}_{\text{user}} + S_{\text{user}} \Delta \overline{\text{Markup}}_{\text{user}} + \Delta S \Delta \overline{\text{Markup}}_{\text{user}} \\
&= \Delta S (\overline{\text{Markup}}_{\text{user}} - \overline{\text{Markup}}_{\text{input}}) + S_{\text{user}} \Delta \overline{\text{Markup}}_{\text{user}} + \Delta S \Delta \overline{\text{Markup}}_{\text{user}}
\end{aligned} \tag{A19}$$

(1) (2) (3)

In the equation above, $\Delta \overline{\text{Markup}}_{\text{Agg}}$ measures the change of aggregate markup of all domestic firms, including the input producers and input users, which can be decomposed as three effects: (1) the resource reallocation between the sectors for input producers and input users $\Delta S (\overline{\text{Markup}}_{\text{user}} - \overline{\text{Markup}}_{\text{input}})$; (2) markup increases by the input users $S_{\text{user}} \Delta \overline{\text{Markup}}_{\text{user}}$; and (3) the firms whose markups increase gain more market shares $\Delta S \Delta \overline{\text{Markup}}_{\text{user}}$. Based on the decomposition, we find that if the average markup of the input producers is not higher than the input users, i.e., $\overline{\text{Markup}}_{\text{user}} \geq \overline{\text{Markup}}_{\text{input}}$, the aggregate markup of all firms will increase, i.e., $\Delta \overline{\text{Markup}}_{\text{Agg}} \geq 0$. This is particularly true for U.S. firms, which tend to outsource labor-intensive and low-markup production processes to other countries and then re-import the inputs and products. Therefore, any reduction in the market share of input producers will not necessarily drive down the aggregate markup. Instead, an increase in aggregate markup will be primarily due to the markup increase by the input users and growth of the firms that adjust their markups upwards.

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