The Effect of Import Competition and Firm Scope on Patent Specialization*

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Abstract

We examine the impact of rising import competition on the composition of innovation within U.S. manufacturing firms between 1990-2017. Rather than focusing on aggregate patent counts, we classify firm-level innovation into incremental, complementary, and exploratory types using patent-level characteristics. We show that source-specific import exposure reallocates innovation across these types. Further, we show that firms with a broader production scope adjust the overall composition of innovation less than narrowly specialized firms when faced with imports from structurally similar sources, consistent with a wider distribution of revenue sources across production segments. These effects are more pronounced in industries whose production characteristics align with those of the exporting source country. Our findings highlight how trade shocks influence the internal structure of innovation with implications for firm adaptability when faced with foreign competition.

Keywords: Imports, Innovation, Patents, Specialization
JEL: F14, O31, D22

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1 Introduction

Global trade has intensified competitive pressure on firms and has changed the way market competition shapes innovation. Firms increasingly compete not only in domestic markets, but with international competitors with production structures and technological capabilities which differ substantially from their own. While the effect of globalization on innovation has received considerable attention in the literature, existing evidence has yet to reach a consensus. More specifically, although the overall relationship between competition and innovation is well documented (Aghion et al. (2005); Grossman and Helpman (1990)), evidence surrounding structural changes within innovation and heterogeneity within competitive exposure is sparse. Understanding why certain competitors generate unique changes in innovative outcomes may help clarify not only firm behavior, but the broader technological direction of modern markets.

This paper seeks to address these sources of heterogeneity by assessing the impact of structurally distinct competitive exposure on outcomes within the process of innovation. We combine data on U.S. imports – classifying the sources of imports by production similarity to U.S. firms – with patent application filed with the United States Patent and Trademark Office (USPTO). Our dataset includes imports from 233 countries between 1990-2017, and more than two million granted patent applications linked to U.S. manufacturing firms. Using these data, we identify unobserved heterogeneity by approximating innovative effort across three latent innovation strategies: incremental, mixed, and exploratory innovation. We then estimate the effects of import exposure at the industry level using an instrumental variables approach, and provide evidence of adjustment across different firm-level innovation strategies caused by differences in the production similarity of competitors within U.S. markets.

1.1 Background

A substantial body of literature examines the effect of trade on innovation. Theoretical work such as Akcigit et al. (2018) emphasize the innovation generating effects of international competition. Empirical findings vary, with estimates emphasizing negative effect associated with international competition (Autor et al. (2020); Liu et al. (2021); Xiao et al. (2025); Liu et al. (2025)), as well as positive and null effects resulting from similar shocks (Bloom et al. (2016); Xu and Gong (2017); Bonnet and Olper (2025)).

From a traditional Schumpeterian perspective, an increase in overall competition may reduce innovation (Schumpeter (1942); Helpman and Krugman (1989)), yet an increase in innovative output at different levels of competitive exposure is a reasonable expectation (Aghion et al. (2005); Ayerst et al. (2023)). In the context of trade, both imports and exports are linked to the competitive dynamics of innovation (Yamashita and Yamauchi (2020)) as well as spillovers to the quality and quantity of innovation (Kang et al. (2025); Liu and Ma (2020)). Evidence surrounding the composition of trade is relatively sparse however. While the net effect of trade on innovation is generally considered to be positive (Coelli et al. (2022); Farooq et al. (2025)), it is unlikely that these effects are uniform across sources, especially at the firm-level (Chakravorty et al. (2024); Melitz and Redding (2021); Shu and Steinwender (2019); Aghion et al. (2005)). While most existing studies treat foreign competitors as homogeneous in the context of innovation, the structure of international competition differs substantially across trading partners. Countries with distinct technological capabilities, factor endowments, and production structures likely exert distinct competitive pressure as well.

The objective of this paper is not only to estimate the effects of trade from heterogeneous sources on innovation, but also to identify compositional changes within innovative outcomes. A second strand of literature examines heterogeneity within the process of innovation. Separate classifications of innovation groups have been discussed in the form of 'exploitation' and 'exploration' (Carvalho et al. (2021)) or 'incremental' and 'radical' innovation (Acemoglu et al. (2022)).

These forms of classification attempt to answer similar questions surrounding firm-level strategies. Work such as Kim (2024), and Braunerhjelm and Thulin (2023) discuss the difference between exploratory and exploitative patents, or 'research' and 'development' in the case of Kim (2024), and identify strategic changes within firms faced with competitive exposure. Prior literature typically groups innovation based on thresholds or continuous patent characteristics, whereas we seek to measure firm-level strategies more directly by approximating the effort inputs associated with different patent-level outcomes.

Motivated by these gaps, we contribute to existing literature in four key ways. First, we provide a data-driven method for approximating unobservable heterogeneity across firm-level characteristics through innovative outcomes to distinguish between latent strategies. Using an EM algorithm (Arcidiacono and Miller (2011); Fraley and Raftery (2002)), we estimate regime probabilities for incremental, mixed, and exploratory innovation based on a vector of patent characteristics including estimated returns, and text-based novelty measures. This approach allows for a transparent approximation of firm-level strategies as observable regimes, and avoids arbitrary thresholds on the distribution of patent characteristics. Further, the EM algorithm plausibly avoids misspecification across innovation strategies, and allows us to observe firms with mixed innovation strategies (March (1991)), which our results suggest are the majority of firms.

Second, we classify import exposure by production similarity with U.S. industries. Rather than measuring competition through general imports, we distinguish between competitors based on how closely each country's export basket resembles U.S. manufacturing intensity. This allows for a more detailed analysis into the structure of competitive forces affecting innovation while isolating differences between domestic competitors and structurally distinct foreign competitors (Krugman et al. (1980); Schott (2008)). Countries with exports similar to the structure of U.S. manufacturing output participate in a higher level of intra-industry trade, while countries with a dissimilar export basket exploit differences in factor endowments and technologies.

Third, we show that the composition of innovation across different firm-level strategies depends

on the structure of international competition. Using an instrumental variables approach, we estimate the effect of industry-level import exposure by source and describe the adjustment process of innovation strategies within firms. Our findings suggest that different forms of competition embodied in the increase of globalization reshapes the way firms search for new technologies.

Fourth, we demonstrate that firms' responses to competitive exposure depend on product scope and the capacity to reallocate innovative effort across many sources of revenue. Combining firm-level measures of product scope and domestic competition (Hoberg and Phillips (2016); Hoberg and Phillips (2025)) with our existing data, we show that firms operating across a broad range of markets exhibit relatively large responses to changes in the competitive environment, as an increased number of effective sources of revenue allow firms to adjust innovation strategies more efficiently. This highlights the role of firm organization in explaining why competitive shocks generate heterogeneous responses across firms.

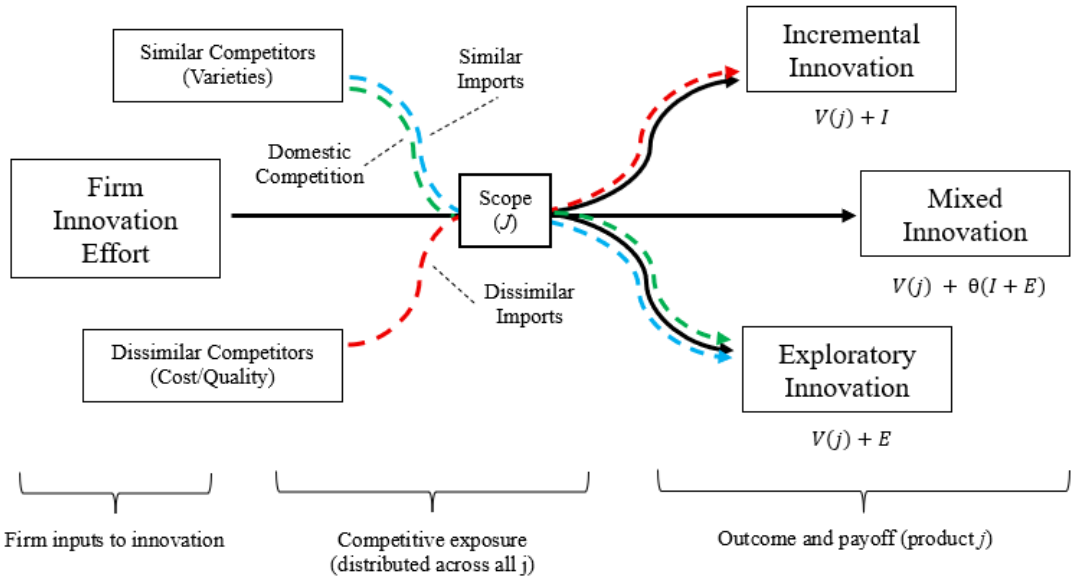
Our baseline results can be summarized as follows. First, competitive pressure from structurally dissimilar countries encourages firms to increase incremental innovation while decreasing exploration. This effect is consistent with quality upgrading rather than a direct escape from competition. Second, competition from structurally similar countries instead increases exploration while decreasing incremental innovation. As firms seek to satisfy consumers' love for variety, a general increase in competition similar to a domestic market expansion pushes firms to explore more novel technologies rather than reinforcing existing products. Finally, these effects differ in magnitude relative to the scope of firms. Firms with a wide scope experience a more diluted form of competitive exposure across many sources of revenue. This encourages firms to pursue exploration[1] while simultaneously improving existing products through a mixture of innovative effort rather than more specialized novel exploration. Firms with a narrow scope instead experience competitive dynamics more directly, which introduces a structural constraint to adjustment across innovation strategies.

[1] It is plausible for some firms to have a comparative advantage in exploration relative to others, which we account for through firm-level controls and fixed-effects.

1.2 Conceptual Framework

We rely on the general framework outlined by Acemoglu et al. (2022) and Akcigit and Melitz (2022) to motivate the underlying mechanism within our empirical results. In each period, firm i must allocate innovative effort across different directions, ranging from incremental improvements on existing products to the exploration of more radical new technologies or product varieties (March (1991)). Rather than treating innovation as an aggregate outcome, firms must choose how to distribute effort across structurally distinct margins, while accounting for firm level characteristics ψ_i and the competitive exposure in an involved industry. For the purpose of simplicity, we assume innovative effort is separable across many products ($j \in J$) and fixed in year t.

Competitive pressure within an industry is not uniform, such that firms face competition from many similar and dissimilar competitors, generating different incentives to innovate. While domestic competitors operate along comparable factor endowments and available technologies, foreign competitors may differ in these inputs. Resembling the intra-industry trade environment described by Krugman et al. (1980), firms compete through product differentiation and variety expansion when faced with foreign competition from structurally similar sources, while more dissimilar competitors encourage firms to innovate through efficiency and quality improvements on existing products.



Firms therefore optimize for value from innovation across all available directions (Klette and Kortum (2004)) within each product or product family j. The key implication of our framework is that while firms allocate effort internally to different innovation strategies, the additional value generated through innovation is specific to the composition of competition within industries. Firms faced with an increased level of competitive pressure from structurally similar competitors will choose to innovate toward the exploratory margin, searching for more varieties to satisfy domestic consumers, while firms faced with an increased level of competition from dissimilar competitors will choose to increment through upgrades to existing goods when foreign alternatives are less substitutable.

This pattern implies that trade shocks do not uniformly affect innovation, but instead reallocate effort across different internal strategies. While the scale of competitive exposure within an industry may effect the level of innovative activity or output, differences in production structure across many competitors plays a more central role in determining how firms adjust innovation portfolios internally.

The remainder of this paper is structured as follows. In Section 2, we outline our sources

of data and measurement of innovation regimes and import heterogeneity. Section 3 describes our empirical specification and discusses the construction of an IV used to identify our baseline results. In Section 4, we present these results and discuss the effect of a continuous exposure to source specific imports on the composition of innovation. Section 5 presents results leveraging a fractional response framework which accounts for the structure of firm-level effort shares. Section 6 provides results accounting for firm scope and it's effects on patenting behavior, while Section 7 concludes with a summary of our findings, and a review of policy implications.

2 Data Sources and Descriptions

As in Grossman and Helpman (1990); Aghion et al. (2005), we consider the process of innovation as a function of competition as well as firm, and industry characteristics. While firm and industry-level trends such as prior innovative activity, and distance from the technological frontier (Egger and Keuschnigg (2015), Amiti and Khandelwal (2013)), are a critical component of innovative outcomes, we focus our analysis on the structure of competitive exposure within manufacturing industries. The purpose of this section is to (i) characterize the environment of foreign competition through U.S. imports, (ii) outline measurement of innovation regimes using patent characteristics including a cluster of mixed innovative outcomes, and (iii) describe the use of firm-level measures including scope, and general market competition (Hoberg and Phillips (2016), Hoberg and Phillips (2025)).

2.1 Imports and Trading Partner Production Similarity

We collect import data from Schott (2008), who provide imports at the HS10 level for the U.S. between 1995-2017 which we link to NAICS industries at the 6-digit level. Schott (2008) provide an account of imports from all available regional sources, which we then separate into economically 'similar' and 'dissimilar' countries through equation (1). More specifically, we leverage theoretical

precedent outlined by new trade theory (see e.g. Krugman et al. (1980)) to isolate the level of relative competitive pressure originating from foreign imports using a measure of 'distance' between production intensities.

$$z_{c,t} = \sum_{j=1}^{J} \left| \frac{L_{j,t}}{L_t} - \frac{M_{j,c,t}}{M_{c,t}} \right| \tag{1}$$

$z_{c,t}$ is the sum of absolute differences between U.S. industry intensity – measured through the ratio of industry employment relative to all industries $L_{j,t}/L_t$ – and the import basket from country c measured through the ratio of industry import value relative to total import value from country c[2]. Higher values of $z_{c,t}$ then indicate countries are more dissimilar to the structure of U.S. manufacturing based on their respective import basket, while lower values indicate an increased level of similarity. Table 2 provides the top-10 countries within each category ranked by U.S. import value between 1990-1994[3].

Since the focus of our analysis is on the form of competition experienced by U.S. manufacturing firms, our core results consider imports by source similarity as a ratio of total industry imports $M^z_{j,t}/M_{j,t}$. We avoid mechanical variation within our results by leveraging the upper and lower terciles of import ratios for both similar and dissimilar country imports. This allows for independent variation within trade related measures, and for our analysis to center on more plausible divisions of production structure. Figure 1 provides a time series representation of import ratios at the industry level. Consistent with our theoretical setting, countries grouped as 'similar' participate in more intra-industry trade with the U.S., which is supported by Figure 2 highlighting the relationship between import shares and industry productivity (Olley and Pakes (1996)). As the productivity of R&D intensive industries increases, the ratio of imports from structurally similar countries relative to all imports is expected to increase as firms participate in more intra-industry trade.

[2]While traditional production distance is constructed using relatively similar ratios such as industry employment or production, we assume Compustat firms provide a reasonable proxy for domestic production intensity within manufacturing industries which allows for a plausible comparison between domestic input structure and foreign output.

[3]We recognize that our baseline measure of production similarity relies on a fixed structure and does not consider changes in group membership across U.S. trading partners. We allow for free entry and exit across similarity groups in robustness checks.

Conceptually, as competition increases from sources similar to U.S. production, the resulting shift in competitive dynamics should resemble an increase in the number of domestic competitors. When competition increases from structurally dissimilar sources, the direction of effects should change away from competition for increased varieties, and toward improvements on the quality of existing products.

2.2 Patent Data and Innovation Regime Measurement

To observe changes in firms' innovation strategies, we approximate innovation 'regimes' from patent-level outcomes. We collect patent data from Kogan et al. (2017) who provide a detailed account of granted patent application from the USPTO linked to public firms in the U.S, as well as measures of citations, and estimated returns at the patent level. We then collect patent text-summaries from the USPTO for all available patents in the dataset, in order to construct a measure of text-based novelty through $TF \times IDF$ weighting[4]. We then link these patents to Compustat firms between 1990-2017. Next, we adapt a version of the EM algorithm (Fraley and Raftery (2002); McLachlan and Peel (2000); Arcidiacono and Miller (2011)), and cluster patent observations on estimated patent returns and textual-novelty. The EM algorithm allows for an approximation of unobserved heterogeneity within patent outcomes which we interpret as three innovation regimes; incremental, mixed, and exploratory innovation. Since inputs of innovative effort are not observed through patent outcomes directly, group membership across innovation 'regimes' is therefore an inferred approximation of unobservable firm-level inputs[5].

Conceptually, incremental innovation should represent relatively less novel patents – generating a relatively small amount of market value embodied in returns – while exploratory innovation

[4]While cosine similarity would provide a more detailed account of pairwise similarity between patents, we opt to leverage aggregate $TF \times IDF$ weights to measure novelty. This provides several advantages, including computational feasibility across a sample of over two million patents, and a more direct measure of technological content 'uniqueness'. Additionally, since patent text summaries are of similar length, any bias resulting from document size is mitigated.

[5]While R&D expenditures are an adequate measure of tangible inputs within firms, they lack the granularity required for more detailed directional measurement distinct from general innovation intensity.

should include patents which are on average more novel and implement newer or less commonly applied technologies while generating a larger amount of value for firms (Acemoglu et al. (2022)); Akcigit and Kerr (2018)). The more specialized groups of incrementation or exploration likely do not capture the majority of innovative outcomes. It seems much more plausible that most patent applications would instead capture a mixture of firm strategies (March (1991)) which can be interpreted as interior outcomes within the distribution of patents. We therefore seek to measure the amount of mixing which occurs through a distinct interior innovation regime.

Allow x_i to represent a vector of patent observations, such that each observation has an identifiable corresponding distribution of characteristics. Within our framework, these characteristics are returns (R_i) and novelty (N_i).

$$x_i = (R_i, N_i) \in \mathbb{R}^2_+ \qquad with \qquad \mu = \frac{1}{n}\sum_{i=1}^{n} x_i, \;\; \Sigma = \frac{1}{n}\sum_{i=1}^{n}(x_i - \mu)(x_i - \mu)^\top \tag{2}$$

where μ is the distribution's mean, and Σ describes variance. Any distribution of characteristics can then be expressed as a function of an innovative outcome or patent $f(p_i)$,

$$f(p_i) = \sum_{g=1}^{G} \gamma_g \, \mathcal{N}(x_i \mid \mu_g, \Sigma_g) \tag{3}$$

where G represents the number of groups. Each $g \in G$ has a specific mixing weight γ_g and a covariance matrix Σ_g. Each observed x_i then follows a normal distribution $\mathcal{N}(\cdot)$.

We update the parameters of each observation based on their posterior group probabilities which allows us to generate the maximum likelihood estimations used to determine mixing probabilities across all $g \in G$ for each observed patent. The estimation of these probabilities in each iteration of the algorithm can be defined as τ_{ig}

$$\tau_{ig} = \frac{\gamma_g \, \mathcal{N}(x_i \mid \mu_g, \Sigma_g)}{\sum_{k=1}^{G} \gamma_k \, \mathcal{N}(x_i \mid \mu_k, \Sigma_k)} \tag{4}$$

To ensure our structure resembles theoretical precedent, we restrict several aspects of the algorithm. First, as emphasized by Arcidiacono and Miller (2011) we provide a set of informative initial mixing weights for clustering, which ensures that the algorithm avoids convergence on arbitrary local optima. These weights are based on a set of theoretical expectations; incremental patents should include iterations on existing technologies, and therefore should not be associated with large estimated returns or high novelty on average, while exploratory patents should reflect relatively more novel and impactful technologies or processes associated with high average returns and novelty. Second, we introduce a third innovation mode which deviates from previous frameworks around incremental and radical or exploratory innovation; mixed innovation. Under an assumption of separable innovative effort Acemoglu et al. (2022), firms may elect to pursue incrementation or exploration simultaneously. This mixing of unobservable inputs would then plausibly produce a distinct category of outcomes which do not neatly fit any existing cluster. This allows us to both assume a general order within a distribution of patent outcomes as firms transition between innovation regimes, and to capture unobservable dynamics within innovating firms while more clearly distinguishing between incremental and exploratory innovation. Initial weights can now be expressed as an ordered condition on the distribution of estimated returns and novelty, $\tau_i^{g,0}$.

$$\tau_i^{I,0} < \tau_i^{M,0} < \tau_i^{E,0} \tag{5}$$

Finally, resulting posterior probabilities τ_i^g are aggregated to a firm-year observation within each group representing the allocation of effort inputs across innovation regimes.

$$\text{Share}_{it}^g = \frac{1}{n_{it}} \sum_{j \in (i,t)} \tau_i^g \tag{6}$$

Table 3 presents the group mean for estimated real returns and text-based novelty, along with the average gap between application year and grant year, number of citations, and the percentage of all application filed within our sample by group.

2.3 Firm Scope and Market Competition Data

While the scale and capital availability of firms directly affects the process of innovation, we assess the impact of firm's scope in distributing competitive pressure among many products or involved industries. Firms with a wide scope may not experience sufficient competitive exposure linked to any single source of revenue through imports which would affect the composition of innovation across regimes, while firms with a narrow scope may react more strongly when faced with increased foreign competition.

We leverage a direct measure of scope at the product level. We collect measures of firm scope relative to available products from Hoberg and Phillips (2025) and Hoberg and Phillips (2016) who calculate firm scope through descriptions. While imports from similar and dissimilar countries introduce additional competitive pressure on domestic manufacturers, omitting domestic competition may confound estimates of the effect of foreign competition. We account for this through a firm-level measure of competitive intensity in the form of HHI from Hoberg and Phillips (2025) and Hoberg and Phillips (2016), which includes the observed firm.

3 Empirical Specification

We estimate how exposure to distinct foreign competitors affects the allocation of innovation effort within firms. Our empirical approach relies on a panel fixed-effects and instrumental variables framework. First, to capture the impact of imports over the entire sample period, the baseline fixed-effects structure can be expressed as equation (7),

$$Share^{g}_{i,j,t} = \alpha + \beta^{g}_{1} Import^{S,D}_{j,t-1} + \gamma \mathbf{X}_{i,j,t} + \delta_i + \eta_t + \varepsilon_{i,j,t} \tag{7}$$

where the share of inferred innovative effort ($Share^{g}_{i,j,t}$)[6] allocated to regime g by firm i in year t is described as a function of previous foreign competition ($Import_{jt-1}$) measured as the share of import exposure within industry j from countries classified as structurally similar (S) or dissimilar (D). β_1 then captures the effect of imports into industry j[7] on the allocation of innovation within regime g. We include a vector of firm-level controls in $X_{i,j,t}$ which are employment and total assets to account for effects associated with firm-size and financial constraints (Egger and Keuschnigg (2015)). Finally, δ_i and η_t control for firm- and year-specific trends while the error term $\varepsilon_{i,j,t}$ captures remaining unobserved variation.

3.1 Instrumental Variables

Import exposure may be correlated with industry demand shocks or technological trends that also influence innovation (Chen et al. (2017)). To account for this, we use an instrumental variables approach using two-stage least squares (2SLS) and isolate exogeneous variation in the supply of imports by exploiting changes in import supply originating from industries that are not directly linked through supply-chain relationships.

Specifically, we construct a neighborhood of industries based on intermediate inputs from the Bureau of Economic Analysis' (BEA) input-output tables for 2007 following the logic of Greenstone et al. (2020). For each industry j we identify the 15 most closely related industries within the domestic supply-chain network as $\mathcal{N}(j)$[8]. Imports into industries within $\mathcal{N}(j)$ are then excluded, and the instrument is constructed as the sum of import exposure in all remaining industries. Fur-

[6] We leverage the share of approximated effort within our baseline specification to avoid assumptions on the level of innovation within firms, as a observed absence of a patent application is not verified as a true absence of a patent filing.

[7] Though the average lag between patent application and grant is around three years within our data, we structure each firm-year observation based on application year. Since the series is updated past the final year of our analysis period, all patent application which were filed between 1995-2017 should be observable. We provide results with additional lag structures within robustness checks.

[8] The size of the excluded neighborhood balances instrument relevance and exclusion. A small set of neighbors risks including structurally dependent industry imports since some industry inputs may still be statistically relevant to the structure of an observed industry. A large set of neighbors threatens instrument relevance, as industry import exposure no longer reliably predicts the scale of imports to an observed industry.

ther, we include the pre-period import intensity between 1990-1994 as weights to capture initial differences in import exposure across all included industries. The resulting instrument for import exposure from structurally similar and dissimilar countries can be expressed as,

$$Z_{j,t-1}^{S,D} = \sum_{k \notin \mathcal{N}(|)}^{\mathcal{J}} w_k^0 M_{k,t-1}^{S,D} \tag{8}$$

where w_k^0 represents a pre-period import share for industry k, and $M_{k,t-1}^{S,D}$ denotes import exposure by source similarity. Within 2SLS estimates, we include $Z_{j,t-1}^{S,D}$ and $Z_{j,t-2}^{S,D}$ as the core set of instruments

The identifying assumption is that imports to industries within critical supply-chain linkages may influence innovation outcomes in an observed industry as firms experience supply-side disruptions, while imports outside these linkages will be unlikely to directly influence innovation in observed industries. Imports outside the direct input structure of any given industry will then plausibly affect innovation only through the production structure of source countries satisfying the exclusion restriction[9].

The first stage regression can then be expressed as equation (9).

$$\widehat{Import}_{j,t-1}^{S,D} = \alpha + \theta Z_{j,t-1}^{S,D} + \gamma \mathbf{X}_{i,j,t} + \delta_i + \eta_t + v_{j,t} \tag{9}$$

and the second stage regression follows our baseline specification and becomes,

$$Share_{i,j,t}^{g} = \alpha + \beta_1^g \widehat{Import}_{j,t-1}^{S,D} + \gamma \mathbf{X}_{ijt} + \delta_i + \eta_t + \varepsilon_{i,j,t} \tag{10}$$

The resulting estimates can be found in Tables 4 and 5 and form our baseline empirical results which distinguish between similar and dissimilar country imports separately.

[9]We consider alternative instruments leveraging variation in exchange rates and HS-10 tariff rates, though both lack sufficient strength across a wide range of import source-countries.

4 Baseline Results

Our baseline results estimate the effect of import exposure on inferred innovation effort within incremental, mixed, and exploratory innovation regimes. Recall from section 2 that these regimes infer the allocation of innovative effort across different firm strategies. Table 4 presents results using import exposure from structurally dissimilar countries as a share of all imports into industry j. Columns (1-3) present results based on panel fixed-effects estimation while columns (4-6) present results using instrumental variables.

Columns (1-3) suggest that imports from countries with structurally dissimilar export baskets to U.S. manufacturing intensity generate an increase in incremental innovation, and a decrease in exploratory innovation. This pattern suggests that when competitive exposure increases from sources which differ substantially from domestic producers in terms of production structure, competition is less likely to introduce new product varieties and more likely to occur through cost advantages. These conditions encourage firms to respond by improving existing products or processes rather than shifting to new technologies entirely. A 1% increase in imports from dissimilar countries generates a 0.17% decrease in exploratory innovation outcomes on average between 1995-2017. While the magnitude of effects appears small, these changes represent shifts in the distribution of innovation effort rather than changes to the overall level of patenting activity.

Since innovation shares follow a simplex constraint such that $I_{i,t} + M_{i,t} + E_{i,t} = 1$, we observe a relative increase in other regimes, with the primary share of opposing effects occurring through incremental innovation. Columns (4-6) using IVs supports this pattern, though estimates on the effect of dissimilar imports are substantially larger, suggesting attenuation bias in fixed-effects estimates. Relative to IV estimates, the percent change in innovative effort is larger than the percent change to competitive exposure through imports. This results suggests that firms respond to competitive shocks by reallocating innovative effort across different technological trajectories producing discrete shifts in innovation strategies rather than marginal adjustments.

Conversely, Table 5 presents results using import exposure from structurally similar countries. Since structurally similar countries possess technologies which closely resemble U.S. manufacturing, competition from such sources is more likely to occur within overlapping production spaces. Estimates presented in columns (1-6) suggest that unlike dissimilar imports, imports from similar source-countries move innovation away from incrementation, and toward exploration. Competition introduced by producers with comparable goods and technologies therefore encourages the development of new varieties through exploration rather than incremental improvements to existing products. The magnitude of effects is smaller however, such that firms shift innovative effort across regimes at a lower rate than shifts in competitive exposure.

Overall, Tables 4 and 5 present evidence consistent with theoretical precedent in that imports from structurally similar countries encourage domestic firms to pursue a competitive advantage through exploring for varieties, while imports from dissimilar countries encourage improvements through adjustments to the quality of existing goods. These results suggest that shifts in innovation strategies depend on whether foreign competitors challenge incumbent firms within existing product spaces or through differences in production structures. The remaining sections explore two additional sources of variation. First, we examine how firm scope affects the adjustment of innovation strategies. Second, we examine whether foreign competition also affects entry into innovation and whether these effects are consistent with the average compositional shifts described by our baseline results.

5 Fractional Response Framework

A potential concern with our baseline linear specifications is the bounded nature of dependent variables. Innovation shares ($Share_{it}^{g} = p_{it}^{g} \in [0, 1]$), for ($g \in I, M, E$), represent the allocation of innovative effort across regimes and are constructed as posterior probabilities from the EM algorithm. Thus, linear models may be misspecified, may fail to capture nonlinearities in the

conditional mean, and can generate fitted values outside the unit interval. To address this, we implement a fractional response framework following Papke and Wooldridge (1996), which models the conditional mean directly. For each regime (g), define

$$\mu_{it}^{g} = \mathbb{E}\left[p_{it}^{g} \mid x_{it}, c_i\right],$$

where (x_{it}) includes lagged import exposure and firm-level controls, and (c_i) captures time-invariant firm heterogeneity. We assume,

$$\mu_{it}^{g} = G\left(x_{it}'\beta_g + c_i\right),$$

where $(G(z) = \frac{\exp(z)}{1+\exp(z)})$ is the logistic function, ensuring that predicted values lie in the unit interval. Let $(Import_{it-1}^{k})$ denote lagged import exposure from source type $(k \in D, S)$, corresponding to structurally dissimilar and structurally similar countries, respectively. Following Krugman et al. (1980), we interpret this decomposition as capturing differences in production structure and substitutability across foreign competitors. The baseline specification for regime (g) is

$$\mathbb{E}\left[p_{it}^{g} \mid Import_{it-1}^{k}, X_{it}, c_i, \tau_t\right] = G\left(\beta_{kg} Import_{it-1}^{g} + X_{it}'\gamma_g + \tau_t + c_i\right),$$

estimated separately for $(k \in D, S)$, where (τ_t) denotes year effects. To account for unobserved heterogeneity that may be correlated with regressors, we implement a correlated random-effects specification. Let

$$\bar{W}_i = \frac{1}{T_i}\sum_{t=1}^{T_i} W_{it},$$

where (W_{it}) contains time-varying explanatory variables. We parameterize the firm effect as

$$c_i = \psi_k + \bar{W}_i'\xi_g + a_{ig},$$

where (a_{ig}) is an idiosyncratic component orthogonal to observed covariates. Substituting into the conditional mean yields

$$\mathbb{E}\left[p_{it}^{g} \mid Import_{it-1}^{k}, X_{it}, \bar{W}_i, \tau_t, a_{ig}\right] = G\left(\beta_{kg} Import_{it-1}^{k} + X_{it}'\gamma_g + \bar{W}_i'\xi_g + \tau_t + a_{ig}\right).$$

As noted previously, import exposure may be endogenous. To address this, we adopt a control function approach. Let import exposure satisfy the reduced-form relationship

$$\text{Import}_{it-1}^{k} = Z_{it-1}'\pi_k + X_{it}'\delta_k + \bar{W}_i'\kappa_k + \tau_t + u_{it}^{k},$$

where $Z_{j,t-1}^{k}$ contains excluded instruments from our baseline specification. Let $(\hat{u}_{it}^{k})$ denote the residual. We augment the fractional response model as

$$\mathbb{E}\left[p * it^{g} \mid Import_{it-1}^{k}, X_{it}, \bar{W}_i, \tau_t, \hat{u}_{it}^{k}\right] = G\left(\beta_{kg} Import_{it-1}^{k} + X_{it}'\gamma_g + \bar{W}_i'\xi_g + \tau_t + \rho_{kg}\hat{u}_{it}^{k}\right),$$

where inclusion of $(\hat{u}_{it}^{k})$ absorbs the endogenous component of import exposure. Since coefficients from nonlinear fractional models are not directly interpretable, we report average partial effects instead. Standard errors are obtained via a clustered bootstrap.

The nonlinear estimates presented in Table 8 reinforce the baseline results and clarify the role of production structure in shaping innovation responses. Exposure to imports from structurally dissimilar countries shifts innovative effort toward incremental and mixed strategies and away from exploratory innovation. In contrast, imports from structurally similar countries exhibit the similar directional patterns as those in Table 4, yet provide a weaker effect once persistent firm heterogeneity and endogeneity are accounted for. Competition from countries with a similar production structure to the U.S. resembles a marginal increase in within-industry competitive pressure, while competition from dissimilar countries acts as a more distinct shock to the relative returns across innovation strategies, inducing reallocation across innovation regimes.

6 Firm Scope and Import Exposure

In this section, we examine the impact of firm scope and the adjustment capacity of innovating firms. Firm scope may influence how strongly firms respond to competition introduced by import exposure since firms that operate across a wide set of product lines may be less exposed to the direct effects of foreign competition. We estimate the effect of firm scope through interactions with import exposure by modifying our baseline specification. These interactions can be expressed as equation 11

$$Share^{g}_{i,j,t} = \alpha + \beta^{g}_{1} Import^{S,D}_{j,t-1} + \beta^{g}_{2} \left(Import^{S,D}_{j,t-1} \times S_{i,t-1} \right) + \beta^{g}_{3} S_{i,t-1} + \gamma \mathbf{X}_{ijt} + \delta_i + \eta_t + \varepsilon_{i,j,t} \tag{11}$$

where $S_{i,t-1}$ is a measure of log-scope from Hoberg and Phillips (2025). The interaction coefficient β^{g}_{2} then captures whether the effect of import exposure on innovation regimes differs across firms with differences in scope. Tables 7 and 8 presents these results.

Columns (1-3) of Tables 6-7 suggest that scope does not uniformly change the effects of import exposure across different types of foreign competitors. As shown in Table 6, import exposure from dissimilar countries is amplified by firm scope, such that firms with a wide scope make larger adjustments across available innovation directions. Import exposure from similar countries, as shown in Table 7 is instead attenuated by scope, such that firms with a wide scope do not adjust innovation strategies as strongly as those with a narrow scope. This suggests that competition from structurally dissimilar countries occurs at the industry level, while competition from structurally similar countries interacts more strongly with firm-level characteristics such as product breadth. Primarily, while the effect of import exposure from similar countries appears to increase a mixture of effort, this effect is relatively small in firms with a wide scope. Our estimates suggest that as scope increases, the effect of import exposure from similar countries decreases further, emphasizing the role of many sources of revenue in diluting the effective level of comparable competition

faced by U.S. firms. Conversely, competition from structurally dissimilar sources is amplified in firms with a wide scope.

7 Conclusion

In this paper, we examine the impact of U.S. imports from structurally similar and dissimilar countries on the composition of innovation within manufacturing firms between 1990-2017. We leverage an EM algorithm to infer latent innovation regimes through observable patent characteristics and estimate the effect of import exposure on the allocation of innovation effort using an instrumental variables approach. Further, we highlight how differences in the structure of international competitors shape outcomes and show that firm scope governs the magnitude of firms' strategic adjustment.

Our results show that the direction of innovation responds to the type of foreign competitors within industries. Import exposure from countries with a structurally dissimilar export basket to U.S. manufacturing intensity encourages firms to concentrate innovative effort on incremental improvements to existing products while reducing overall exploration. In contrast, import exposure from structurally similar countries shifts effort toward exploration and away from incremental activity. These results suggest that competition from similar producers resembles an increase in domestic competitive pressure, whereas competition from dissimilar producers encourages firms to upgrade the quality of existing goods.

We further show that firm scope moderates the magnitude of these adjustments. Firms with a wide production scope respond less to import exposure from similar countries. Since multi-product firms already generate variety across many product lines, competitive pressure which resembles domestic competition generates smaller shifts in innovation strategies. In contrast, the response to competition from structurally dissimilar competitors is largely unaffected by scope, suggesting that fundamental changes in the competitive structure of markets generates similar adjustment across

firms regardless product breadth.

Our findings highlight that the effect of foreign competition through trade depends both on the intensity of competitive exposure as well as the structure of competitors themselves. More broadly, these results emphasize that heterogeneity among foreign competitors plays a key role in shaping the direction of technological change within domestic markets.

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Table 1: Similarity Comparison by Group Membership

	Mean	S.D.	Min.	Max.	Number of Countries
Dissimilar	1.067	0.030	1.024	1.143	77
Similar	0.977	0.024	0.874	0.995	78
Total	1.017	0.044	0.874	1.143	233

Note: Similarity scores are constructed from import-basket distances measuring comparability to U.S. industry production intensity.

Table 2: Top-10 Import Source Regions by Production Similarity Category

Rank (Import Value)	Dissimilar ($z > z_{Q_{66}}$)	Similar ($z < z_{Q_{33}}$)
1	China	Canada
2	Taiwan	Mexico
3	South Korea	Germany
4	Singapore	United Kingdom
5	Hong-Kong	France
6	Saudi Arabia	Italy
7	Malaysia	Brazil
8	Venezuela	Switzerland
9	Thailand	Netherlands
10	Nigeria	Belgium

Note: Countries are ranked by aggregate import value across all available NAICS industries during the baseline period. Similarity scores are constructed from import-basket distances measuring comparability to U.S. industry production intensity. Country names and codes follow the definitions reported in the U.S. Census Bureau's *Schedule C – Country Codes and Descriptions*.

Table 3: Posterior-weighted descriptive statistics by latent innovation regime.

Regime (i)	μ^R	μ^N	$\text{year}^G - \text{year}^A$	μ^{cites}	π_i
Incremental	0.10	-0.40	2.92	9.29	0.18
Mixed	2.36	-0.23	3.04	15.30	0.63
Exploratory	3.02	1.10	3.01	17.67	0.20

Note: Summary statistics based on an EM alogorithm from granted patent applications between 1990-2017. The sample consists of over 2.1 million total patents. Initialization is provided through a quantile distribution of the vectors space x_i at the 25th and 75th percentiles.

Table 4: Effect of Dissimilar U.S. Imports on Innovation Shares (1995-2017)

	FE-OLS			*IV-2SLS*		
	(1) Incremental	(2) Mixed	(3) Exploratory	(4) Incremental	(5) Mixed	(6) Exploratory
$\text{Dissimilar Imports}_{j,t-1}$	0.119***	0.050	-0.170***	0.353***	0.925	-1.278**
	[0.039]	[0.042]	[0.054]	[0.133]	[0.592]	[0.575]
Log-Employment	-0.260	1.515**	-1.255**	0.008	1.618**	-1.625**
	[0.477]	[0.682]	[0.519]	[0.563]	[0.795]	[0.719]
Log-Capital	-0.957***	0.462	0.495	-0.919***	0.877**	0.041
	[0.218]	[0.357]	[0.397]	[0.272]	[0.379]	[0.390]
Constant	7.513***	53.720***	38.767***	-	-	-
	[1.349]	[2.211]	[2.879]			
N	14464	14464	14464	12857	12857	12857
R^2	0.695	0.816	0.848	-0.006	-0.105	-0.211
First-stage F	-	-	-	12.37	12.37	12.37
Hansen-J p-value	-	-	-	0.154	0.418	0.497

Note: * p $<$ 0.1, ** p $<$ 0.05, *** p $<$ 0.01. Clustered standard errors in parentheses. Standard errors are clustered by firm and industry. All regressions include firm and year fixed effects. Columns (4-6) include the first-stage F-statistic and the Hansen-J test p-value. Constant omitted in columns (4-6) due to fixed-effects structure. Partial R^2 is not well defined in columns (4-6), and replaced by a standard centered-R^2. Reported values of innovation are approximated shares of effort by category measured through patent characteristics. Outcomes reflect only firms which filed a patent application between 1995-2017.

Table 5: Effect of Similar U.S. Imports on Innovation Shares (1995-2017)

	FE-OLS			*IV-2SLS*		
	(1) Incremental	(2) Mixed	(3) Exploratory	(4) Incremental	(5) Mixed	(6) Exploratory
$\text{Similar Imports}_{j,t-1}$	-0.078***	0.007	0.071	-0.198***	-0.701**	0.900***
	[0.028]	[0.056]	[0.063]	[0.076]	[0.299]	[0.284]
Log-Employment	-0.247	1.498**	-1.250**	0.038	1.800**	-1.838***
	[0.467]	[0.681]	[0.519]	[0.550]	[0.803]	[0.684]
Log-Capital	-1.019***	0.437	0.582	-1.119***	0.346	0.773*
	[0.225]	[0.353]	[0.385]	[0.254]	[0.459]	[0.456]
Constant	15.407***	55.047***	29.545***	-	-	-
	[2.066]	[2.652]	[2.537]			
N	14464	14464	14464	12857	12857	12857
R^2	0.695	0.816	0.847	0.003	-0.076	-0.129
First-stage F	-	-	-	11.28	11.28	11.28
Hansen-J p-value	-	-	-	0.310	0.379	0.306

Note: * p $<$ 0.1, ** p $<$ 0.05, *** p $<$ 0.01. Clustered standard errors in parentheses. Standard errors are clustered by firm and industry. All regressions include firm and year fixed effects. Columns (4-6) include the first-stage F-statistic and the Hansen-J test p-value. Constant omitted in columns (4-6) due to fixed-effects structure. Partial R^2 is not well defined in columns (4-6), and replaced by a standard centered-R^2. Reported values of innovation are approximated shares of effort by category measured through patent characteristics. Outcomes reflect only firms which filed a patent application between 1995-2017.

Table 6: Effect of Dissimilar U.S. Imports and Scope on Innovation Shares (1995-2017) (*FE-OLS*)

	(1) Incremental	(2) Mixed	(3) Exploratory
$\text{Dissimilar Imports}_{j,t-1}$	0.069*	-0.036	-0.033
	[0.040]	[0.078]	[0.083]
$\text{Dissimilar Imports}_{j,t-1} \times \text{Scope}_{i,t-1}$	0.025**	0.039*	-0.064***
	[0.010]	[0.024]	[0.018]
$\text{Scope}_{i,t-1}$	-0.594**	-1.410	2.004*
	[0.288]	[0.987]	[1.024]
Log-Employment	-0.215	1.368*	-1.154**
	[0.541]	[0.709]	[0.521]
Log-Capital	-1.094***	0.542	0.553
	[0.260]	[0.387]	[0.423]
_cons	9.633***	55.840***	34.527***
	[1.699]	[3.057]	[3.841]
N	13327	13327	13327
R^2	0.710	0.817	0.849

Note: * p $<$ 0.1, ** p $<$ 0.05, *** p $<$ 0.01. Clustered standard errors in parentheses. Standard errors are clustered by firm and industry. All regressions include firm and year fixed effects. Reported values of innovation are approximated shares of effort by category measured through patent characteristics. Outcomes reflect only firms which filed a patent application between 1995-2017.

Table 7: Effect of Similar U.S. Imports and Scope on Innovation Shares (1995-2017) (*FE-OLS*)

	(1) Incremental	(2) Mixed	(3) Exploratory
$\text{Similar Imports}_{j,t-1}$	-0.032	0.121	-0.089
	[0.027]	[0.074]	[0.070]
$\text{Similar Imports}_{j,t-1} \times \text{Scope}_{i,t-1}$	-0.026**	-0.058***	0.084***
	[0.011]	[0.019]	[0.016]
$\text{Scope}_{i,t-1}$	1.531**	2.767***	-4.298***
	[0.771]	[1.044]	[0.683]
Log-Employment	-0.206	1.315*	-1.108**
	[0.530]	[0.710]	[0.526]
Log-Capital	-1.159***	0.535	0.624
	[0.260]	[0.384]	[0.406]
Constant	13.575***	48.513***	37.912***
	[2.201]	[3.616]	[2.896]
N	13327	13327	13327
R^2	0.710	0.818	0.849

Note: * p $<$ 0.1, ** p $<$ 0.05, *** p $<$ 0.01. Clustered standard errors in parentheses. Standard errors are clustered by firm and industry. All regressions include firm and year fixed effects. Reported values of innovation are approximated shares of effort by category measured through patent characteristics. Outcomes reflect only firms which filed a patent application between 1995-2017.

Table 8: Effect of Import Composition on Innovation Shares

	Incremental	Mixed	Exploratory
$\text{DissimilarImports}_{j,t-1}$	0.211***	0.617***	-0.726***
	[0.081]	[0.160]	[0.144]
$\text{SimilarImports}_{j,t-1}$	-0.163*	0.056	0.048
	[0.093]	[0.178]	[0.164]
N	12988	12988	12988

Note: * p $<$ 0.1, ** p $<$ 0.05, *** p $<$ 0.01. Bootstrap standard errors in brackets. All regressions include previously used controls (capital and employment) as well as a control function described previously and year variables.

Table 9: Effect of U.S. Imports by Source Similarity with Domestic Market Competition on Innovation Shares (1995-2017) (*FE-OLS*)

	(1) Incremental	(2) Mixed	(3) Exploratory
$\text{Dissimilar Imports}_{j,t-1}$	0.079*	0.096	-0.176**
	[0.040]	[0.064]	[0.069]
$\text{Similar Imports}_{j,t-1}$	-0.035	0.070	-0.036
	[0.025]	[0.084]	[0.094]
Domestic Market (HHI)	-0.909	1.534	-0.624
	[1.091]	[1.192]	[1.195]
Log-Employment	-0.373	1.460**	-1.087*
	[0.503]	[0.730]	[0.571]
Log-Capital	-1.017***	0.515	0.502
	[0.283]	[0.373]	[0.418]
Constant	11.173***	49.374***	39.453***
	[2.351]	[5.448]	[5.116]
N	13021	13021	13021
R^2	0.719	0.810	0.841

Note: * p $<$ 0.1, ** p $<$ 0.05, *** p $<$ 0.01. Clustered standard errors in parentheses. Standard errors are clustered by firm and industry. All regressions include firm and year fixed effects. Reported values of innovation are approximated shares of effort by category measured through patent characteristics. Outcomes reflect only firms which filed a patent application between 1995-2017.

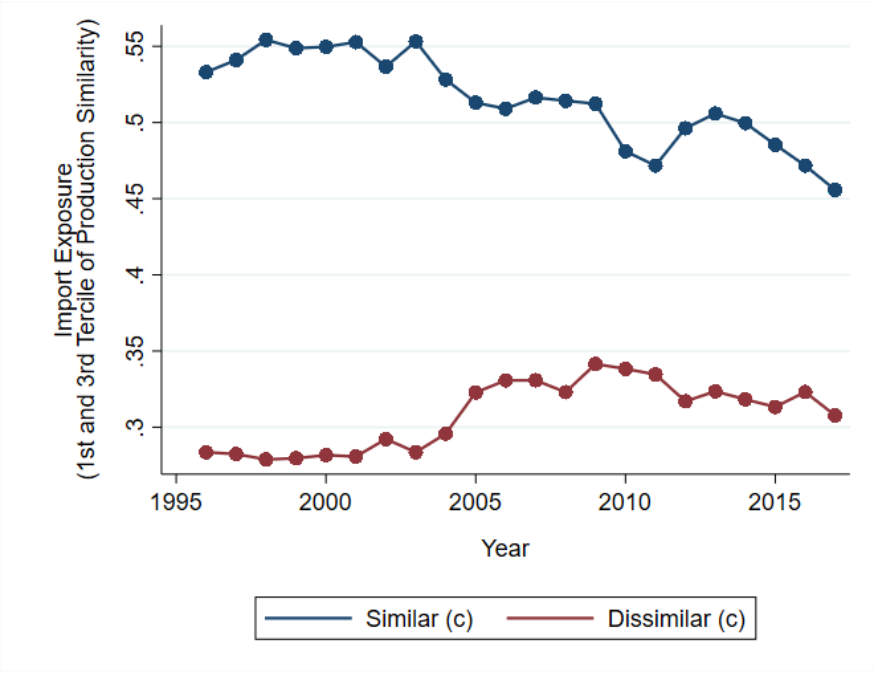


Figure 1: Import exposure as a share of total across all NAICS industries linked to Compustat firms between 1995-2017. Country similarity based on the relative distance of production from U.S. manufacturing intensity based on equation 1.

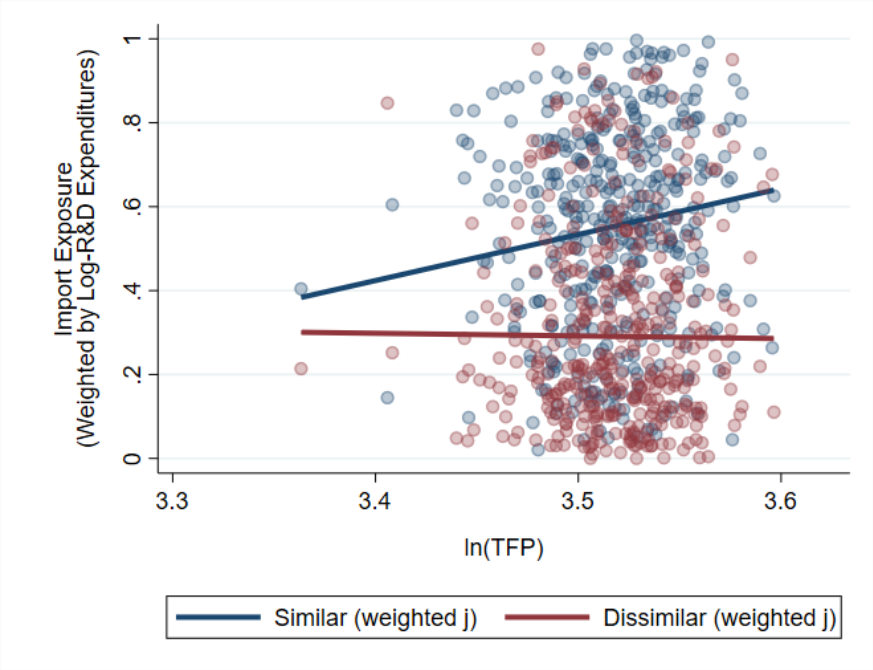


Figure 2: Import exposure as a share of total across all NAICS industries linked to Compustat firms between 1995-2017 by Olley-Pakes log-productivity. Linear relationships weighted by industry log-R&D expenditures