Foreign Import Competition and Process Innovation[*]

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Abstract

I examine how Chinese import competition changes the type of innovation U.S. firms pursue. Using an instrumental variable strategy, I find that rising imports from China lead U.S. firms to shift their innovative efforts toward process innovation, which focuses on cost reduction, rather than the creation of innovative products. This shift is stronger when product differentiation is difficult, when firms operate in ex-ante riskier environments, and for more labor-intensive firms. In contrast, the effect is weaker for firms that already have alternative ways to reduce costs. I also show that process innovation buffers firms against the adverse effects of import competition. Firms with higher process innovation experience smaller declines in profitability and in the growth of sales, assets, employment, and capital when import penetration rises. When Chinese import competition is high, announcement returns at patent grant dates are higher for process innovation-related patents, especially in industries in which product differentiation is limited. Overall, these findings provide new insights on firms' innovation-related responses to foreign competitive pressure.

Key words: Chinese import competition; process innovation; product similarity; firm resilience

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I. Introduction

Chinese import penetration has had substantial effects on the U.S. economy, including reduced manufacturing employment, lower wages, and increased plant closures (Autor, Dorn, and Hanson 2013; Acemoglu et al. 2016; Pierce and Schott 2016; Bernard, Jensen, and Schott 2006). Firms respond to this competitive pressure through various channels, with innovation emerging as one of the key margins (Bloom, Draca, and Van Reenen 2016; Autor et al. 2020).

The evidence on innovation, however, is mixed. Bloom, Draca, and Van Reenen (2016) find that European firms more exposed to Chinese imports increase patenting, IT adoption, and total factor productivity. Autor et al. (2020), studying U.S. firms, find that patent production declines in response to the same competition. A broader literature suggests that the effect of competition on innovation is not monotonic, varying with a firm's competitive position and the balance between escaping competition and the erosion of innovation rents (Aghion et al. 2005).

Most studies treat innovation as a single margin, focusing on whether import competition raises or lowers innovative effort overall. However, there is little evidence on which type of innovation firms pursue in response to foreign price competition and on the conditions that shape that choice.

In this paper, I examine how rising Chinese import competition affects U.S. manufacturing firms' allocation of innovative effort between process and product innovation. Product innovation supports differentiation by introducing new features or higher quality, while process innovation reduces costs and improves production efficiency (Scherer 1982; Cohen and Klepper 1996; Klepper 1996). The distinction matters because the two types of innovation serve different strategic purposes and can help firms to respond in different ways to competitive pressures.

The main empirical challenge in identifying the causal effect of Chinese import competition on US firms' innovation choices is that this competition can be endogenous to these firms' innovation and other financial policy decisions. To address this concern, I employ an instrumental variable strategy following Autor, Dorn, and Hanson (2013) and Hombert and Matray (2018). The instrument replaces U.S. Chinese import penetration with contemporaneous Chinese import penetration in eight other high-income countries. The identifying assumption is that the common within-industry component of Chinese export growth across these markets reflects supply-side forces originating in China rather than import-demand conditions correlated across destination countries. Under this assumption the instrument isolates the Chinese-driven component of U.S. import growth and is orthogonal to U.S. demand shocks that independently influence firm innovation.

With this exogenous variation in hand, I turn to how U.S. firms respond to Chinese import competition. Because U.S. imports from China far exceed U.S. exports to China, the shock operates through import competition rather than export demand, and I treat it as an intensification of price competition in U.S. firms' output markets. Such competition gives firms an incentive to innovate in order to escape it (Aghion et al. 2005). The question is what form that response takes.

When firms can climb the quality ladder, they escape low-cost competition by differentiating their products. This route is not equally open to all firms. If products are close substitutes and the quality ladder is short, low-cost entrants can approximate a firm's existing features and the return to further differentiation is limited (Khandelwal 2010). As price competition intensifies, the relative payoff to reducing unit costs rises, and process innovation becomes a more attractive way to defend margins.

Consistent with this prediction, I find that Chinese import competition tilts the composition of innovation toward process innovation in U.S. manufacturing firms. A one-standard-deviation increase in import penetration raises the process share of innovation by approximately 5.2 to 6.2 percent. This is not a substitution away from product innovation. Both process and product patenting rise with import competition, but process claims grow substantially faster, so the share of innovative effort devoted to process increases.

The result is robust across a range of specifications, including a stacked first-difference design following Autor, Dorn, and Hanson (2013), industry-level estimations, and alternative patent-weighting schemes. Two checks bear directly on identification. A pre-trend test finds no differential trend in the process share of innovation across industries that later faced greater import competition, and dynamic selection bounds following Bloom, Draca, and Van Reenen (2016) remain positive and significant under conservative assumptions about firm exit, ruling out differential attrition as an explanation.

I then examine the mechanisms through which import competition shifts firms toward process innovation. The first test focuses on cross-sectional variation in product similarity. If the shift is driven by intensified price competition, it should be more pronounced in high product-similarity industries, where competition is more price based and product differentiation is much harder to achieve. In such environments the returns to cost-reducing process innovation rise relative to product innovation. Consistent with this prediction, using the Hoberg and Phillips (2016) product similarity measure, I find that the shift toward process innovation is more pronounced in high-product-similarity industries. Further, the effect is more pronounced for focused (single-scope) firms operating in high product-similarity industries. These firms have even

fewer opportunities to reallocate resources across business segments and must therefore make adjustments within their core production process.

Next, I consider the effect of firm-level uncertainty. Product innovation typically depends on uncertain market acceptance and requires longer development and commercialization horizons. Process innovation, however, generates internal and predictable efficiency gains that materialize over a shorter period. Under heightened import competition, which compresses margins and raises the cost of unsuccessful innovation, firms facing greater ex-ante uncertainty would have stronger incentives to favor innovation with more reliable payoffs. If so, the shift toward process innovation should be stronger for firms operating in riskier environments. Consistent with this prediction, using four different measures of volatility, I show that firms with higher volatility tilt toward process innovation more.

Cross-sectional variation in firms' labor intensity should also matter. China's comparative advantage is concentrated in labor-intensive goods, so Chinese import competition is most harmful for U.S. firms whose production relies more on labor. For such firms, labor accounts for a larger share of total costs, and reductions in unit labor costs translate disproportionately into improved margins. As a result, the benefits from increasing the process share of innovation should be greater for labor-intensive firms. Supporting this view, using two different measures of labor intensity, I show that the process tilt is significantly larger for firms in labor-intensive industries.

I also consider the impact of alternative cost-reduction channels. Process innovation is valuable to firms facing import competition because it lowers production costs. However, for firms that already have alternative ways to reduce their costs, the marginal benefit of additional process innovation should be smaller. Vertically integrated firms, for instance, can improve efficiency internally by coordinating production stages and reducing transaction costs across the value chain

(Williamson 1971, 1979; Frésard, Hoberg, and Phillips 2020). Similarly, firms that source inputs from China already benefit from lower foreign factor costs (Hoberg and Moon 2017; Bena and Simintzi 2025). If process innovation serves as a means of reducing costs, the response should be weaker for firms that already possess these alternatives. In line with this prediction, I document that the shift toward process innovation is significantly attenuated for vertically integrated firms and for firms that already source inputs from China.

Beyond documenting the shift in process innovation itself, I examine whether a higher process share is associated with greater resilience to import competition. Consistent with prior evidence, I find that increased Chinese import competition is associated with declines in firm profitability and growth across sales, assets, gross profit, employment, and capital investment. Importantly, I show that these adverse effects are mitigated for firms with a higher process share in their innovation portfolio. The pattern holds across all six performance dimensions and is economically significant, suggesting that process innovation is associated with improved firm outcomes under import pressure.

Finally, I examine cumulative abnormal returns around patent grant dates to shed light on whether capital markets recognize the strategic value of process innovation in the presence of intense import competition. Consistent with this notion, I provide novel evidence that the market responds more positively to process-oriented patents for firms in high-product-similarity industries facing greater import competition. Product-oriented patents, by contrast, do not receive a comparable premium in these settings. This market-based evidence complements the other findings on the strategic benefits of process innovation in response to import competition.

This paper contributes to several strands of the literature. First, it adds a new dimension to the debate on how import competition affects innovation. Bloom, Draca, and Van Reenen (2016)

find that European firms increase innovation in response to Chinese imports, while Autor et al. (2020) show that U.S. firms reduce it. Both papers focus on the level of innovation and neither examines its composition. I show that in the U.S., the composition of innovation shifts toward process improvements aimed at cost reduction, and that this compositional shift has real consequences for firm outcomes.

Second, I add to work on strategic responses to import competition. Prior studies document adjustment through restructuring, product differentiation, and increased patenting (Hombert and Matray 2018; Autor et al. 2020; Aghion et al. 2024). I document that the innovation response is not only a matter of how much firms innovate but the type of innovation they pursue. Accounting for whether the response takes the form of product or process innovation is essential to understanding how firms innovate under foreign competition.

Third, the paper advances the literature on the strategic roles of product and process innovation (Cohen and Klepper 1996; Klepper 1996). Recent studies examine how various economic shocks shape the innovation mix. For instance, artificial intelligence adoption boosts product innovation and rising labor costs encourage process innovation (Babina et al. 2024; Bena, Ortiz-Molina, and Simintzi 2022; Bena and Simintzi 2025). This paper provides novel evidence that low-cost import competition from China induces a shift of innovation toward process innovation, and it connects this finding to the broader trade literature by showing that this is associated with firms better absorbing the adverse effects of import competition on performance.

Finally, the paper contributes more broadly to research on product market competition and firm strategy by showing how product similarity, firm scope, and organizational boundaries jointly shape innovation responses to foreign competition (Hoberg and Phillips 2016; Frésard, Hoberg, and Phillips 2020). The results highlight that firms' innovation strategies are not determined solely

by their own characteristics, but also by the competitive landscape and organizational options available to them.

The remainder of the paper proceeds as follows. Section II develops the conceptual framework and empirical predictions. Section III describes the data and variable construction. Section IV discusses the identification strategy. Section V presents the empirical results and robustness tests. Section VI concludes.

II. Conceptual Framework and Empirical Predictions

A. The Nature of the China Import Shock

China's transition from central planning to a market economy generated one of the largest trade shocks in modern history. Rural-to-urban migration of over 150 million workers, access to previously banned foreign technologies and capital goods, and the entry of multinational enterprises expanded Chinese manufacturing capacity across a broad range of industries (Naughton 2007; Hsieh and Klenow 2009). China's accession to the World Trade Organization in 2001 further accelerated this process by granting most-favored-nation status and removing quotas on Chinese exports to WTO members (Branstetter and Lardy 2006).

Autor, Dorn, and Hanson (2013) show that this shock operates on U.S. labor markets primarily through the import competition channel. Chinese productivity growth and falling trade costs affect U.S. firms through two channels. The first is increased competition in domestic product markets, where Chinese imports displace demand for domestically produced goods. The second is increased Chinese demand for U.S. exports.

In theory, these two forces could offset each other, but because of persistent trade imbalances between the two countries, they do not. China's average current-account surplus in the 2000s was approximately 5 percent of GDP, a figure roughly equal to the contemporaneous U.S.

current-account deficit. The import competition effect therefore dominates the export demand effect, and the net result is a reduction in domestic manufacturing employment, output, and wages in exposed industries. Chinese imports also include intermediate inputs that can benefit domestic firms through lower input costs (Goldberg et al. 2010). However, the evidence suggests that these input gains do not offset the negative output-market effects for the typical U.S. manufacturing firm (Autor, Dorn, and Hanson 2013; Autor et al. 2020).

The competitive pressure from the China shock therefore takes a specific form. It is price-based, it operates through increased effective substitutability between domestic and imported goods, and it is concentrated in labor-intensive sectors where China's comparative advantage is most pronounced (Amiti and Freund 2010). This characterization of the shock matters for understanding its implications for innovation, because different types of competitive shocks have different implications for the composition of innovative effort, as the next subsections show.

B. Innovation Responses to the China Shock: The Level Debate

A large literature examines how U.S. and European firms respond to Chinese import competition through innovation, but this work has focused on whether import competition raises or lowers the overall level of innovative activity.

Bloom, Draca, and Van Reenen (2016) study twelve European countries from 1996 to 2007 and find that firms more exposed to Chinese imports increase patenting, IT adoption, R&D expenditure, and total factor productivity. They decompose this aggregate effect into within-firm and between-firm channels. On the within-firm margin, surviving firms increase their innovative activity. On the between-firm margin, low-technology firms shrink and exit while high-technology firms are relatively sheltered, reallocating economic activity toward more technologically advanced producers. The within and between effects are roughly equal in magnitude for patents

and together account for approximately 14 percent of European technology upgrading over 2000 to 2007.

Autor et al. (2020) study U.S. firms over a similar period and find the opposite result. Rising import competition reduces sales, profitability, R&D expenditure, and patent production. The decline in patents is roughly proportional to the contraction of sales, employment, capital, and R&D, suggesting that firms scale down all activities in response to competitive pressure rather than selectively cutting innovation. Importantly, the negative effect concentrates on firms that were initially less profitable and less capital-intensive, while stronger firms are less affected. These findings are robust to three different identification strategies, including the ADH instrument, the Pierce and Schott (2016) PNTR tariff-gap instrument, and the Bloom, Draca, and Van Reenen (2016) MFA quota instrument.

Aghion et al. (2024) offer a partial reconciliation of these opposing findings. They emphasize that the effect of competition on innovation depends on the dispersion of technological capabilities across firms. When dispersion is low, as appears to be the case in many European industries, intensified competition encourages firms to innovate to escape competition. When dispersion is high, as in U.S. industries (Bartelsman, Haltiwanger, and Scarpetta 2013; Hashmi 2013), more competition may stifle innovation among laggard enterprises.

Hombert and Matray (2018) show that U.S. firms with a larger pre-existing R&D stock are more resilient to Chinese import competition because they can use their R&D to differentiate their products, which is also consistent with heterogeneous responses depending on initial firm characteristics.

Across all of these studies, innovation is treated as a single margin. Whether firms patent more or less, or spend more or less on R&D, the composition of innovative activity between

product and process innovation receives little attention. This is the margin the present paper examines.

The product-versus-process margin has received attention in other contexts. Recent work shows that economic shocks other than trade can reshape the innovation mix. Bena, Ortiz-Molina, and Simintzi (2022) and Bena and Simintzi (2025) show that rising labor costs encourage process innovation. Babina et al. (2024) find that artificial intelligence adoption boosts product innovation. Whether foreign price competition reshapes the innovation mix in a similarly predictable way, however, remains an open question. The present paper takes it up directly.

C. Why Import Competition Should Shift Innovation Toward Process

Firms allocate innovative effort between product and process innovation based on their expected returns, and theoretical work in industrial organization predicts that this allocation depends systematically on the nature and intensity of competition (Scherer 1982; Cohen and Klepper 1996; Klepper 1996). Rosenkranz (2003) provides the most directly relevant theoretical framework. She models a duopoly in which firms simultaneously choose process innovation (reducing marginal production costs) and product innovation (reducing product substitutability) before competing in quantities. Consumers have a preference for product variety, and the degree of product substitutability determines the intensity of price competition.

The central result from these papers is that the two types of innovation generate opposite competitive externalities. Process innovation is a strategic substitute. One firm's cost reduction hurts its rival because it shifts demand and profits toward the more efficient producer. However, product innovation is a strategic complement. Greater differentiation benefits firms because it softens price competition and allows each to serve its own segment of the market more profitably.

This asymmetry in externalities has direct implications for how the innovation portfolio responds to changes in the competitive environment. When product substitutability is high, price competition is intense and demand is more responsive to cost advantages. In this environment, the marginal return to process innovation rises relative to product innovation because the competitive reward for lower costs is large while the reward for further differentiation is diminished by the difficulty of sustaining it against low-cost rivals.

Rosenkranz (2003) also shows that when market potential is large, as in the early stages of a product life cycle, firms favor product innovation. When the competitive environment shifts toward price-based rivalry and products are already somewhat differentiated, the portfolio tilts toward process innovation. This distinction between market-expansion shocks and price-competition shocks is important for the present paper. A market-expansion shock, such as increased export demand from China, would shift the innovation portfolio toward product innovation. The China shock, however, is predominantly a price-competition shock operating through the import channel with persistent trade imbalances, so the conditions favor process innovation.

Boone (2000) provides a complementary prediction. He develops a framework in which competitive pressure reallocates profits across firms according to their relative efficiency, sorting firms into categories based on their profit levels and their incentives to improve. As competitive pressure intensifies, the profit function becomes more sensitive to cost differences. The marginal return to cost reduction increases because competition amplifies the profit differential between low-cost and high-cost producers. Firms therefore face stronger incentives to invest in process innovation, which improves their cost position, relative to product innovation, which primarily shifts the level of profits without changing the sensitivity of profits to costs.

In Boone's framework, firms that already possess cost advantages (what he calls "complacent" firms) face weaker incentives for further cost reduction, while firms with room for improvement (the "eager" and "struggling" categories) face the strongest incentives. This heterogeneity across firms in their incentives to invest in process innovation will be relevant for the cross-sectional predictions that follow.

Vives (2008) provides additional comparative statics on how market structure shapes cost-reduction incentives. He shows that an increase in product substitutability raises equilibrium cost-reduction effort per firm, provided that market size does not contract. The mechanism works through two channels. First, higher substitutability intensifies price competition, raising the competitive reward for lower costs. Second, demand reallocation toward more efficient firms amplifies the return to cost reduction. Both channels increase the incentive for process innovation. Because the Chinese import shock compresses domestic market share and margins rather than expanding them, the substitutability effect dominates any market-size effect, and the prediction is that process innovation increases.

Applying these models to Chinese import competition shocks yields a clear prediction. The competitive pressure from Chinese imports is price-based and raises effective substitutability, which is precisely the environment in which Rosenkranz (2003), Boone (2000), and Vives (2008) predict the innovation mix should shift toward process. The innovation mix should therefore tilt toward process innovation.

D. Empirical Predictions

The discussion above implies that the intensity of price-based competition plays an important role in shaping firms' choice between product and process innovation, and that competitive shocks which raise the substitutability between domestic and foreign goods, such as

the rise of Chinese import competition, will be especially likely to shift innovative effort toward process innovation. Taking these predictions to the innovation composition, I have the following empirical predictions:

1. Chinese import penetration is positively related to the share of process innovation in U.S. manufacturing firms' patenting. The increase reflects a disproportionate rise in process innovation relative to product innovation, with both types increasing in response to import competition but process claims growing substantially more.
2. The shift toward process innovation is concentrated in industries with higher product similarity, and within such industries it is further amplified for focused (single-scope) firms.
3. The shift toward process innovation is stronger for firms operating in riskier environments, as proxied by cash-flow volatility and by total, idiosyncratic, and unlevered return volatility.
4. The shift toward process innovation is more pronounced for labor-intensive firms.
5. Firms with alternative cost-reduction channels, namely vertically integrated firms and firms that already source inputs from China, show a weaker tilt toward process innovation.
6. Firms with a higher share of process-oriented patents experience smaller declines in profitability and in the growth of sales, assets, gross profit, employment, and capital when import penetration rises.
7. Three-day cumulative abnormal returns around patent grant dates are higher for process-oriented patents granted to firms in high-similarity industries facing greater import competition.

These predictions are consistent with established theories of competition and innovation, and the remainder of the paper takes these predictions to the data.

III. Data and Sample Construction

A. Key Variables

1. Process Innovation

Process innovation is measured using the claim-level classification of U.S. patents developed by Ganglmair, Robinson, and Seeligson (2022), who classify independent claims as either process or product based on the preamble and body of each patent. Patents follow a hierarchical order in which the first claim defines the primary invention, while subsequent claims typically describe variants or dependent features of that invention. My main measure follows Bena and Simintzi (2025) and classifies a patent as a process patent when its first (primary) claim is a process claim. For each firm-year, I then compute the ratio of process patents to total patents filed by the firm, which represents the fraction of the firm's patents aimed at production-related improvements rather than product novelty or quality.

As an alternative measure, I use the share of process claims in total claims, defined as the number of process claims divided by the total number of claims across all patents the firm files in that year. The claim-level alternative captures the intensity of process orientation within patents rather than only classifying patents based on their primary claim, and it serves as a robustness check on the main first-claim measure. I use patent filing dates rather than grant dates to align with the timing of innovation decisions, since filing reflects when the firm commits to a line of innovation while grants occur later in time and depend on administrative processing at the USPTO. Firms must have at least one patent during the sample period to be included.

2. Chinese Import Penetration

I measure industry-level exposure to Chinese competition using import penetration, defined as U.S. manufacturing imports from China (in 2020 dollars) divided by industry employment in a fixed base year (1999). Chinese import data come from the BACI database (CEPII), which provides harmonized bilateral trade flows at the product level. I aggregate imports to the three-digit SIC level using concordance files between HS96 product codes and SIC codes. Using employment in a fixed base year rather than contemporaneous employment avoids the endogeneity concern that employment itself responds to Chinese import competition, which would introduce a mechanical correlation between the denominator and the underlying competitive shock. Employment data come from the County Business Patterns (CBP) dataset. The sample is restricted to manufacturing industries (SIC codes 2000 to 3999).

For the instrumental variable strategy, I construct the instrument using Chinese import penetration to eight other high-income countries following Autor, Dorn, and Hanson (2013) and Hombert and Matray (2018). The eight countries are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland, all of which experienced substantial growth in Chinese imports over the sample period, but whose domestic demand conditions are plausibly uncorrelated with U.S. firm-level innovation decisions.

Figure 1 illustrates the growth of Chinese exports over the sample period. Panel A plots total Chinese exports to each of the nine destination countries, namely the United States and the eight instrument countries, from 1996 to 2020. The United States is the largest single destination, but exports to all nine countries have grown substantially over the period.

Panel B plots Chinese exports to the United States against the aggregate sum of exports to the eight other countries. The two series move closely in parallel, which is consistent with Chinese

export growth being driven by common supply-side factors originating within China rather than by U.S.-specific demand conditions. These patterns motivate using the eight-country aggregate as an instrument for U.S. import exposure, since the component of Chinese export growth that appears across multiple unrelated destination markets is unlikely to reflect shocks specific to any single country.

Figure 2 plots Chinese import penetration for both the United States (solid line) and the eight other high-income countries (dashed line) across twelve broad manufacturing industries from 1996 to 2020. Import penetration varies substantially in levels across industries, ranging from low tens of thousands of dollars per worker in Food and Tobacco to over a million dollars per worker in Apparel, Leather, and Electronic Equipment.

Chinese imports in most industries follow a common pattern of rising through roughly 2008 to 2012 before stabilizing or declining. Within each industry, the U.S. and other-country series move in parallel, which further supports the identifying assumption that the variation in U.S. import exposure driven by Chinese supply conditions is shared across high-income destinations. This combination of cross-sectional variation across industries and time-series variation within industries is the primary source of identification in the regressions that follow.

B. Sample Construction

The sample consists of U.S. manufacturing firms (SIC 2000 to 3999) in Compustat from 1996 to 2020. I drop firm-years with missing or non-positive total assets or sales. Following Hombert and Matray (2018), I require firms to have at least three consecutive years of non-missing data in order to focus on established firms whose innovation decisions reflect ongoing strategic choices rather than short-lived entry or exit.

Firms must also have at least one patent during the sample period so that the process share can be computed. When a firm's historical three-digit SIC code is missing in a given year, I fill it using the firm's most recent non-missing SIC code to maintain industry continuity over time. The main regression sample therefore contains 19,720 firm-year observations. Sample size varies across specifications when additional cross-sectional variables are required, such as product similarity, cash-flow volatility, labor intensity, vertical integration, and China input sourcing, each of which is drawn from different underlying data sources with their own coverage.

For industry-level specifications, I collapse the data to the three-digit SIC industry by year, computing the industry-level process share as the ratio of total process patents to total classified patents in each industry-year. This yields 2,202 industry-year observations. For the stacked first-difference specification following Autor, Dorn, and Hanson (2013), I divide the sample into four sub-periods (1996 to 2001, 2001 to 2007, 2007 to 2013, and 2013 to 2019) and compute the within-period change in the process share and in import penetration for each firm. This yields 2,189 firm-period observations.

C. Summary Statistics

Table 1 reports summary statistics for the main regression sample. The table presents means and standard deviations for the full sample as well as separately for firms in high- and low-product-similarity industries, with the last two columns reporting the difference in means and the corresponding t-statistics. The process share based on the first-claim classification has a mean of 0.322 in the full sample, indicating that roughly one third of patents filed by manufacturing firms over this period are primarily process-oriented.

The process share is higher in high-similarity industries, at 0.354, than in low-similarity industries, at 0.265, a difference of 8.9 percentage points that is statistically significant. This cross-

sectional pattern is consistent with process innovation being more important in settings where differentiation is harder to achieve. Table 1 also reports import penetration, log total assets, R&D over total sales, log firm age, and market-to-book for the full sample and separately by similarity group. High-similarity and low-similarity firms differ significantly along several of these dimensions, particularly in firm size, R&D intensity, firm age, and market-to-book, though notably not in import exposure, where the difference is small and statistically insignificant. The regressions include the relevant controls and fixed effects to absorb these differences.

Figure 3 plots the annual process patent share from 1996 to 2020 for high-product-similarity industries, low-product-similarity industries, and the full sample. High-product-similarity firms exhibit a persistently higher process share throughout the sample period. This pattern is consistent with the prediction that Chinese import competition, which intensified over this period, drives a larger process shift in industries where differentiation is more difficult. The figure provides descriptive motivation for the regression analysis, which formally identifies the causal effect of import competition on the process share using the instrumental variables strategy described in the next section.

IV. Identification Strategy

A. Endogeneity Concerns

This section describes the instrumental variable strategy used to address endogeneity and presents first-stage validation. Identification is central to interpreting the relationship between Chinese import competition and process innovation as causal rather than correlational. Two concerns arise in particular. First, import penetration may be correlated with unobserved industry or firm characteristics that also affect innovation choices, such as technological opportunity, demand growth, or underlying productivity trends, which would produce omitted variable bias in

ordinary least squares estimates. For example, an industry experiencing rapid technological progress may simultaneously attract more Chinese imports (because rising domestic productivity frees up market space) and shift its innovation mix for reasons unrelated to trade, generating a spurious correlation.

Second, reverse causality is a concern because firms that cut innovation for unobserved reasons may become less competitive over time, which in turn could raise import penetration in their industry. Both concerns would bias estimates of the effect of import competition on innovation choices. The direction of the bias is ambiguous in general but likely works against finding a positive effect of imports on process innovation. If positive technology shocks in U.S. industries crowd out Chinese imports (because domestic firms become more competitive), then OLS would understate the true positive effect of imports on process innovation. This is consistent with the pattern documented by Bloom, Draca, and Van Reenen (2016), who find that IV estimates are uniformly larger than OLS for the effect of Chinese imports on European innovation. To address these issues, I use an IV strategy following Autor, Dorn, and Hanson (2013) and Hombert and Matray (2018), which isolates variation in U.S. import exposure driven by supply-side factors within China.

B. Instrument Construction

The instrument is Chinese import penetration in eight other high-income countries: Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland. These countries have broadly comparable levels of economic development and manufacturing structure, but their import growth from China is unlikely to be driven by U.S.-specific demand conditions. Bilateral trade data come from the BACI database using HS96 classification, mapped to SIC codes consistently with the U.S. measures. For each country, import penetration is constructed

analogously to the U.S. measure and normalized by U.S. base-year employment in 1999, ensuring comparability across the instrument and the endogenous variable.

The identifying assumption is that Chinese export growth to these countries is driven primarily by supply-side shocks in China that affect export capacity across destinations, such as productivity growth, WTO accession, and the gradual removal of trade quotas. Under this assumption, the instrument isolates plausibly exogenous variation in U.S. import exposure arising from Chinese supply conditions.

An important feature of the empirical design is that the instrument varies at the industry level while the main regressions are estimated at the firm level. All firms within the same three-digit SIC industry receive the same value of import penetration and the same value of the instrument. In the first stage, many firms therefore share the same values of both the endogenous variable and the instrument, and the effective number of independent observations for identification is the number of industry-year cells rather than the number of firm-year observations. If standard errors are not adjusted for this clustering, the first-stage F-statistic will be inflated and the precision of the IV estimates will be overstated.

To address this, I cluster all standard errors at the three-digit SIC industry level throughout the analysis, which accounts for both the within-industry correlation induced by the industry-level instrument and any serial correlation in industry-level shocks over time. To verify that the instrument is strong at the level where it varies, I also estimate the first stage at the industry-year level with industry and year fixed effects. The Kleibergen-Paap F-statistic at the industry level is well above the Stock and Yogo (2005) critical value of 16.38 for 10 percent maximal IV size. The firm-level Kleibergen-Paap F-statistic is substantially larger, reflecting the repeated values of the

instrument across firms within the same industry, and overstates the effective instrument strength. The industry-level F-statistic provides the more conservative and appropriate benchmark.

Hombert and Matray (2018) face the same issue and describe an alternative approach in which they estimate the first stage at the industry level without including firm-level controls, obtain predicted values of import penetration, and then use those predicted values in the firm-level second stage. I also implement this industry-level first stage and obtain similar results. I nevertheless report the standard two-stage least squares setup in which the first stage includes the same controls and fixed effects as the second stage, so that the instrument's predictive power is evaluated conditional on those controls rather than unconditionally. The similarity of results across the two approaches provides additional confidence that the mismatch between the level of variation in the instrument and the level of observation in the regression is not driving the findings.

In specifications that include interactions of import penetration with firm or industry characteristics, such as high product similarity, cash-flow volatility, labor intensity, vertical integration, or China input sourcing, the endogenous regressors include both import penetration itself and its interactions with these moderators. I therefore instrument all terms involving import penetration with the corresponding terms built from the instrument, namely the level of the instrument and its interactions with the same moderators (for example, instrumented IP × High Sim or instrumented IP × Risk). This approach keeps the exclusion restriction consistent across the level and interaction terms. In these specifications, there are two endogenous variables and two instruments, and I report first-stage F-statistics for each endogenous variable separately to verify that both are well identified.

C. Threats to Identification

There are three specific threats to the validity of the instrument. Each is relevant for the present analysis, and I address them in turn. First, a potential concern with the instrumental variables strategy is that demand shocks may be correlated across high-income countries. For example, if consumers in both the United States and Europe simultaneously increase their demand for certain goods (such as consumer electronics), imports from China would rise in multiple markets for demand-driven reasons rather than because of Chinese supply shocks. In this case, the instrument would be correlated with unobserved demand conditions, and both the OLS and IV estimates could be biased.

I address this concern directly. Correlated demand shocks are most plausible in a narrow set of industries where rich-country demand moves together, with computers the clearest case, since booms in IT demand raise imports in the United States and other high-income countries for reasons unrelated to Chinese supply (Autor, Dorn, and Hanson 2013). If such demand were driving the estimated shift toward process innovation, excluding this industry should attenuate the result. It does not. Appendix Table A1 shows that dropping the computer industry leaves the estimate essentially unchanged, indicating that the result is not an artifact of demand shocks common to high-income countries.

The second threat is that U.S. productivity shocks could be driving the growth in Chinese imports. If the U.S. has poor productivity growth in a particular industry, domestic production falls and imports from China rise in both the U.S. and European markets, because the U.S. also exports less to Europe in that industry, and European consumers substitute toward Chinese goods. This would contaminate the instrument because the increase in other-country imports from China would partly reflect U.S. supply conditions rather than Chinese supply conditions.

Several pieces of evidence argue against this threat being quantitatively important. China's productivity growth over the sample period has been far more rapid than that of the U.S. or any other major economy. Brandt, Van Biesebroeck, and Zhang (2012) estimate average annual TFP growth in Chinese manufacturing of 8.0 percent over 1998 to 2007, compared with 3.9 percent for the U.S. Furthermore, between 1992 and 2007, China accounted for three quarters of the worldwide growth in manufacturing value added in low- and middle-income nations (Autor, Dorn, and Hanson 2013). The growth in Chinese exports therefore appears to be strongly related to factors specific to China rather than to productivity deterioration in the U.S.

The third threat is that technology shocks common to all high-income countries could simultaneously drive both the growth in Chinese imports and changes in innovation composition. For example, if automation in wealthy countries makes their labor-intensive industries less competitive, these industries may both import more from China and shift their innovation mix for reasons unrelated to trade. This threat is difficult to rule out entirely, but several features of the analysis mitigate it. I include firm and year fixed effects in all specifications, which absorb any time-invariant firm characteristics and any aggregate shocks common to all firms in a given year. I also report pre-trend falsification tests in Appendix Table A2 that examine whether the process share was already changing in the expected direction before Chinese import competition accelerated. If common technology shocks were driving both imports and innovation composition, I would expect to see a pre-existing relationship, which the falsification tests can detect, but there is no detectable pre-trend relationship.

D. Instrument Validity and Diagnostic Tests

For the instrument to be valid, two conditions must hold. First, the relevance condition requires that the instrument be strongly correlated with the endogenous variable. Table 2 column

(1) reports the first-stage results, showing a coefficient of 0.899 on the other-high-income-country instrument with a standard error of 0.053 and a first-stage R-squared of 0.974, all of which support relevance. Because the first stage is estimated with the same fixed effects and controls as the second stage, the instrument's predictive power is established conditional on those controls rather than in isolation.

I report the Kleibergen-Paap rk Wald F-statistic as the appropriate test for weak instruments when standard errors are clustered. The firm-level F-statistic is well above conventional thresholds, though as discussed in Section IV.B, the industry-level F-statistic provides the more conservative benchmark, and it largely exceeds the Stock and Yogo (2005) critical value of 16.38 for 10 percent maximal IV size as well. The Anderson-Rubin Wald test, which is robust to weak instruments, also strongly rejects the null of no effect.

Second, the exclusion restriction requires that the instrument affect process innovation only through its effect on U.S. import penetration and not through any other channel. This restriction is not directly testable, but its plausibility can be assessed through supporting evidence and economic reasoning. The exclusion restriction is plausible if two conditions hold. First, Chinese exports to the United States and to other high-income countries must be driven primarily by common supply-side factors originating within China rather than by destination-specific demand. Second, demand or productivity shocks in the eight other high-income countries must be uncorrelated with U.S.-specific determinants of innovation.

The timing of major supply-side shocks, including China's WTO accession and the removal of Multi-Fiber Agreement quotas, together with the high correlation of Chinese export growth across destination countries with different demand structures, is consistent with supply-side factors being the dominant driver. If country-specific demand conditions were the primary source of

variation, I would expect greater divergence in Chinese export growth patterns across destinations, which is not what the data show.

Figure 4 plots the change in Chinese import penetration to the United States against the change in import penetration to the eight other high-income countries from 1996 to 2020, following Hombert and Matray (2018). Each point is a three-digit SIC industry, and penetration is measured in 2020 dollars per base-year (1999) worker. The fitted slope is 1.06, a nearly one-to-one relationship between U.S. and other-country import exposure. This close co-movement across destinations with heterogeneous demand conditions is more easily explained by common supply-side drivers within China than by coincidental demand shocks across multiple unrelated markets, supporting both the relevance of the instrument and the exclusion-restriction logic.

To provide direct evidence on pre-trends, I conduct a falsification test at the industry level. I regress the change in the industry-level process share in the pre-period (1996 to 2001) on the subsequent change in import penetration in the post-period, using both a shorter window (2001 to 2006) and a longer window (2001 to 2020), estimated by both OLS and IV. The coefficients are essentially zero and statistically insignificant across all four specifications. The process share was not trending differently in industries that would later experience greater Chinese import competition. This result is consistent with the instrument capturing the causal effect of import competition on innovation composition rather than pre-existing trends in the process share.

E. Empirical Specification

The empirical specifications are as follows:

$$ImportPen_{i,t} = \alpha + \beta \cdot OtherHighIncomeImportPen_{i,t} + \gamma X_{i,t-1} + \delta_i + \theta_t + \epsilon_{i,t} \quad (1)$$

$$ProcessShare_{i,t} = \alpha + \beta \cdot \widehat{ImportPen}_{i,t-1} + \gamma X_{i,t-1} + \delta_i + \theta_t + \epsilon_{i,t} \quad (2)$$

where $ProcessShare_{i,t}$ is the share of process-oriented patents, measured using either the first-claim classification or the claim-level alternative; $ImportPen_{i,t}$ is Chinese import penetration at the firm or industry level; $OtherHighIncomeImportPen_{i,t}$ is the instrument based on Chinese exports to the eight other high-income countries; $X_{i,t-1}$ is a vector of lagged firm-level controls; and δ_i and θ_t are firm and year fixed effects, respectively. Equation (1) is the first stage, and equation (2) is the second stage in which the instrumented value of import penetration replaces the endogenous regressor.

V. Empirical Results

A. First-Stage Results: Instrumental Variable Validation

Table 2 column (1) reports the first-stage regression of Chinese import penetration in the United States on Chinese import penetration to eight other high-income countries, alongside the second-stage IV and OLS estimates in columns (2) through (5). Column (1) shows that the coefficient is positive and highly significant, and the first-stage R-squared indicates that the instrument, together with firm and year fixed effects and lagged controls, explains nearly all of the variation in U.S. import penetration. The Kleibergen-Paap rk Wald F-statistic, the appropriate weak-instrument test under clustered standard errors, is 285, well above the Stock and Yogo (2005) critical value of 16.38 for 10 percent maximal IV size.

Because the instrument varies at the industry level while the regression is estimated at the firm level, the firm-level F-statistic reflects repeated values of the instrument across firms within the same industry, as discussed in Section IV. Re-estimating the first stage at the industry level yields a Kleibergen-Paap F-statistic of 78, which remains well above the critical value and provides the more conservative benchmark for instrument strength.

B. Main Results: Chinese Import Competition and Process Innovation

Columns (3) and (5) in Table 2 present the second-stage instrumental variable estimates of the effect of Chinese import penetration on process innovation. In columns (2) and (3) the dependent variable is the fraction of a firm's patents whose primary claim is a process claim, estimated by OLS and IV respectively; in columns (4) and (5) the dependent variable is the share of process claims across all claims in the firm's patents filed in that year estimated by OLS and IV. In both IV specifications, the coefficient on instrumented import penetration is positive and statistically significant at the one percent level, indicating that firms exposed to greater Chinese import competition tilt their innovation toward process improvements. The IV estimates are modestly larger than the corresponding OLS estimates, consistent with OLS attenuation from measurement error or from endogeneity bias working against a positive effect, as discussed in Section IV.

The magnitude is economically meaningful. Because import penetration enters the regression standardized by its firm-level standard deviation, the estimates in columns (3) and (5) imply that a one-standard-deviation increase in import penetration raises the process share by approximately 1.7 to 2.0 percentage points, or about 5.2 to 6.2 percent relative to the sample mean of 0.322. This represents a sizable shift in the innovation mix for the average firm. The finding supports the hypothesis that cost reduction becomes the dominant competitive margin when low-cost imports intensify price pressure, and that firms respond by tilting innovative effort toward process improvements.

C. Patent and Claim Counts

Table 3 examines whether the rise in the process share arises from a disproportionate increase in process innovation or from a contraction in overall patenting. The dependent variables

in Table 3 are the log of one plus the number of patents (column 1), total claims (column 2), process claims (column 3), and product claims (column 4), and the log of the ratio of process to product claims (column 5).

The coefficient on instrumented import penetration is positive and significant for both overall patenting and total claims (columns 1 and 2 respectively), so import competition does not reduce the volume of innovative activity at the firm level. Process claims rise significantly, and product claims rise as well, though the product effect is weaker and significant only at the ten percent level (columns 3 and 4 respectively). Column (5) shows that the coefficient on the log ratio of process to product claims is positive and significant, confirming that process claims grow faster than product claims. Both margins of innovation therefore increase with import competition, but process innovation grows disproportionately. Therefore, the shift in the process share documented in Table 2 reflects a genuine tilt of inventive effort toward cost-reducing improvements rather than a mechanical consequence of falling product innovation.

D. Cross-Sectional Heterogeneity: Product Similarity and Focused Firms

To examine heterogeneity in the response, I estimate interaction specifications of the form:

$$ProcessShare_{i,t} = \alpha + \beta_1 \widehat{ImportPen}_{i,t-1} + \beta_2 (\widehat{ImportPen \times Moderator})_{i,t-1} + \gamma X_{i,t-1} + \delta_i + \theta_t + \epsilon_{i,t} \quad (3)$$

I interact import penetration with a set of firm- and industry-level moderators, instrumenting both import penetration and each interaction term using Chinese imports to the eight other high-income countries. In the first cross-sectional tests, I test the effect of product similarity and being a focused firm within a high product similarity industry. If the shift toward process innovation is a strategic response to limited differentiation opportunities, it should be stronger in high-product-similarity industries, and particularly for focused firms that cannot pivot to other lines of business. Table 4 tests this prediction.

Column (1) in Table 4 interacts import penetration with an indicator for high-similarity industries. High Sim indicator equals one for firms in three-digit SIC industries with above-median average product similarity, measured from firms' 10-K product descriptions using the Hoberg and Phillips (2016) product similarity measure. The interaction is positive and significant. The process-innovation response is therefore concentrated in high-similarity industries. In these industries, a one-standard-deviation increase in import penetration raises the process share by roughly 8% relative to the sample mean.

Column (2) shows that focused firms alone exhibit no differential response, with the interaction of import penetration and focused firm insignificant, consistent with firm focus mattering only when combined with limited differentiation options at the industry level. Focused Firm is an indicator equal to one if the firm operates in only a single product market and zero otherwise, based on the Hoberg and Phillips (2025) 10-K-based product-market scope measure.

Column (3) reports the triple interaction. The coefficient on import penetration interacted with both high similarity and focused firm is positive and significant. Focused firms operating in high-similarity industries, therefore, increase their process share. The response is strongest precisely for focused firms in high-similarity industries, the firms for which escaping price competition through product differentiation is most difficult and for which reallocating activity across business segments is not an option. This pattern supports the view that the shift toward process innovation is more pronounced when firms cannot easily differentiate their products.

E. Cross-Sectional Heterogeneity: Ex-Ante Risk

Product innovation is typically more uncertain than process innovation, since it depends on consumer acceptance, market reception, and longer payback horizons, whereas process innovation generates more predictable returns through internal efficiency gains. If firms tilt toward

the safer innovative margin when uncertainty rises, the response to import competition should be stronger for firms already facing higher ex-ante uncertainty. Table 5 interacts import penetration with an indicator for high firm-level uncertainty, measured using four alternative proxies: cash-flow volatility (column 1), total stock return volatility (column 2), idiosyncratic return volatility (column 3), and unlevered return volatility (column 4).

Across all four measures, the base effect of instrumented import penetration remains positive and significant, and the interaction with the high-uncertainty indicator is positive and significant. Firms facing greater ex-ante uncertainty therefore exhibit a larger shift toward process innovation in response to import competition. The result holds across every uncertainty proxy, supporting the prediction that firms favor the more predictable returns of process innovation when their underlying business uncertainty is already elevated.

F. Cross-Sectional Heterogeneity: Labor Intensity

Import competition exerts downward pressure on domestic labor demand and costs, which raises the return to innovations that economize on labor. The logic of directed technical change implies that firms will direct innovative effort toward technologies that reduce reliance on the factor whose competitive disadvantage is most binding (Acemoglu 2002). For labor-intensive firms, labor accounts for a larger share of production costs, so process innovations that lower unit labor costs are particularly valuable under import pressure.

Table 6 tests this prediction using two industry-level measures of labor intensity. The first measure, used in column (1), is total industry employment scaled by industry value added, computed at the three-digit SIC level using data from the Bureau of Economic Analysis (BEA) Industry Economic Accounts (Palacios 2013). Value added, also known as GDP-by-industry, measures an industry's contribution to national GDP and consists of employee compensation, taxes

on production and imports less subsidies, and gross operating surplus. Industries with more employees per dollar of value added rely more heavily on labor in production relative to the output they generate. The second measure, used in column (2), is constructed from Compustat data as the number of employees scaled by property, plant, and equipment, aggregated across firms to the three-digit SIC industry level. This measure captures labor intensity relative to the industry's stock of physical capital. In each year, an industry is classified as labor intensive if the corresponding measure is above the annual median.

In both specifications, the base effect of instrumented import penetration is positive and significant, and the interaction with the high labor-intensity indicator is positive and significant. Thus, as predicted, the process-innovation response is stronger in more labor-intensive industries.

G. Cross-Sectional Heterogeneity: Cost-Reduction Substitutes

Firms that can already achieve cost efficiencies through other channels should have weaker incentives to shift innovative effort toward internal process innovation, since the marginal return to new process technologies is lower when alternative cost-reduction mechanisms are already in place. In the terminology of Boone (2000), these firms lie closer to the complacent region, where existing efficiency advantages reduce the pressure to invest in further cost improvements. Table 7 interacts import penetration with an indicator for vertically integrated firms (column 1) and an indicator for firms that source inputs from China (column 2).[3]

[3] One concern about the results in this section is that vertical integration and China input sourcing are endogenous firm choices that may be jointly determined with a firm's process innovation, which complicates their interpretation as moderators. One piece of evidence mitigates this concern directly: both indicators are only weakly correlated with the process share. The Pearson correlations are −0.15 for vertical integration and −0.06 for China sourcing, and the corresponding Spearman correlations are −0.14 and −0.04. The moderators are therefore not mechanically capturing a firm's process innovation, which limits the scope for the interaction to reflect selection on that dimension.

The base effect of instrumented import penetration remains positive and significant in both columns, so the baseline effect continues to hold. The interaction terms are negative and significant in both specifications. The process-innovation response is therefore weaker for vertically integrated firms and for firms that already source inputs from China. These findings indicate that vertical integration and offshore input sourcing function as substitutes for domestic process innovation, lowering the marginal benefit of additional process-oriented effort when import competition intensifies.

H. Firm Performance: Process Innovation as a Buffer

To test whether process innovation buffers firms against import competition, I estimate the following specification:

$$Performance_{i,[t:t+3]} =$$

$$\alpha + \beta_1 ImportPen_{i,t-1} + \beta_2 \left(ImportPen_{i,t-1} \times ProcessShare_{i,t-1}\right) + \gamma X_{i,t-1} + \delta_i + \theta_t + \epsilon_{i,t} \qquad (4)$$

where $Performance_{i,[t,t+3]}$ is either ROA or the three-year growth rate in sales, assets, gross profit, employment, or property, plant, and equipment; $ProcessShare_{i,t-1}$ is the lagged process-patent share; and the coefficient of interest is β_2, which captures the buffering effect of process innovation. If process innovation helps firms reduce costs and improve efficiency, it should mitigate the adverse effects of import competition on firm performance.

Table 8 reports the results. The coefficient on instrumented import penetration is negative across all six outcomes, confirming the adverse effect of Chinese import competition on profitability and medium-run growth. The interaction between import penetration and the lagged process share, however, is positive and significant across the outcomes. Firms with a higher process share are therefore able to mitigate some of the negative effects from rising Chinese

imports. The pattern complements the compositional evidence by suggesting that the shift toward process documented in the main results is associated with meaningful differences in realized firm outcomes under competitive pressure.

I. Market Valuation: Cumulative Abnormal Returns Around Patent Grants

Finally, I test whether the stock market recognizes the strategic value of process innovation when it is most relevant, that is, when firms face intense import competition in high-similarity industries where differentiation is difficult. If investors understand the economic logic developed in Section II, they should price process patents more favorably precisely in these settings. I estimate the following specification for announcement returns:

$$CAR_{i,grant} = \alpha + \beta_1 ProcessShare_{i,grant} + \beta_2\left(ProcessShare_{i,grant} \times HighSimilarity_{i,t} \times ImportPen_{i,t}\right) + \gamma X_{i,t} + \epsilon_{i,grant} \quad (5)$$

Where $CAR_{i,grant}$ is the three-day cumulative abnormal return around the patent grant date, calculated over the window of one trading day before to one trading day after the grant, and $ProcessShare_{i,grant}$ is process-patent share. Abnormal returns are estimated using a market model with a 253-day estimation window, a minimum of 100 required return observations, and a 63-day gap before the event to avoid contamination from pre-grant information leakage.

Table 9 reports the results. Column (1) shows that the process share alone is positively associated with abnormal returns, indicating a general market premium for process-oriented inventive activity. Column (2) adds import penetration and its interaction with the process share; the interaction is insignificant. Column (3) includes the triple interaction of the process share with import penetration and high similarity. The coefficient on the triple interaction is positive and significant at the one percent level. The market therefore assigns a higher value to process-oriented patents precisely in the conditions where the earlier results show the shift toward process

innovation is strongest. Thus, this evidence is consistent with the view that the compositional shift reflects a value-relevant strategic response for firms.

J. Robustness

1. Excluding the Computer Industry

A concern with the instrument is that in some sectors, import demand shocks may be correlated across high-income countries, which would violate the exclusion restriction. Computers are the clearest such case, since demand shocks are plausibly correlated across countries owing to common innovations in information technology, and patenting in computers expanded rapidly well before Chinese imports rose. Although the outcome here is the process share, a ratio less mechanically tied to patenting levels than patent counts, I verify that the result is not driven by this sector.

Table A1 reports the baseline IV specification excluding firms in the computer industry. The coefficient on instrumented import penetration remains positive and significant. The result is therefore not driven by the sector where correlated demand is most plausible.

2. Pre-Trend Falsification

A standard concern with the ADH instrument is that industries differing in exposure to Chinese import competition may have been on divergent innovation trajectories before the China shock materialized. If industries that would later face large import surges were already shifting toward process innovation for reasons unrelated to trade, such as automation trends or secular changes in industry life cycles, the IV estimates would capture pre-existing dynamics rather than a causal response to import competition.

To address this, I conduct a falsification test at the industry level, regressing the change in the industry-level process share over the pre-period (1996 to 2001) on the subsequent change in

import penetration over two post-period windows (2001 to 2006 and 2001 to 2020), by both OLS and IV. Table A2 reports the results. The coefficients are close to zero and insignificant across all four specifications. Thus, the process share was not trending differentially in industries that would later experience greater Chinese import competition, which is consistent with the instrument capturing the effect of import competition rather than pre-existing trends.

3. Industry-Level Estimation

The firm-level specifications include firm fixed effects and therefore identify within-firm changes in the process share. The aggregate industry-level process share, however, can move through two channels: within-firm adjustment by surviving firms and between-firm reallocation through the entry and exit of firms with different innovation compositions. Bloom, Draca, and Van Reenen (2016) emphasize this distinction and find that within-firm and between-firm effects contribute roughly equally to the aggregate technology upgrading induced by Chinese imports in Europe. If between-firm selection were the sole driver of the industry-level pattern here, the within-firm estimates would overstate the effect on individual firms.

Table A3 reports IV regressions at the three-digit SIC industry-year level, where the process share is computed as total process patents divided by total classified patents. In the patent-weighted specification, the coefficient on instrumented import penetration is positive and significant; in the unweighted specification it is positive but imprecisely estimated. The patent-weighted result confirms that the aggregate shift toward process innovation is detectable at the industry level and not solely a within-firm phenomenon.

4. Dynamic Selection Bounds

A concern specific to firm-level panel estimation is that Chinese import competition may induce firm exit, and exiting firms may differ systematically in their innovation composition from

survivors. If firms with low process shares are disproportionately pushed out of the sample, the within-firm estimates would be biased upward as the surviving sample increasingly consists of high-process-share firms. Bloom, Draca, and Van Reenen (2016) address this by constructing worst-case lower bounds. I follow their approach but impose several alternative assumptions about the counterfactual process share of exiting firms, providing a range of bounds rather than a single scenario.

Table A4 reports the results. Pseudo observations are assigned to firms that exit before the end of the panel under four alternative assumptions about their post-exit process share. The coefficient on instrumented import penetration remains positive and significant under every assumption. Under the most conservative case, in which exiting firms are assigned their last observed process share, the estimate falls to about two-thirds of the baseline but remains significant at the one percent level. The baseline estimate lies within the range of the bounds. Dynamic selection bias therefore does not appear to drive the result.

5. Stacked First Differences

The baseline annual panel imposes a constant effect of import competition on the process share across years and a stationary error structure over the full 1996 to 2020 period. These assumptions may be restrictive, since the intensity of the China shock varied across sub-periods, accelerating around WTO accession in 2001, peaking in the mid-2000s, and moderating after the financial crisis. Autor, Dorn, and Hanson (2013) address analogous concerns by estimating their specification in stacked first differences.

Table A5 reports this specification. The sample is divided into four sub-periods, and the within-period change in the process share is regressed on the within-period change in import penetration, instrumented using the corresponding change in other-country import penetration,

with start-of-period controls and period fixed effects. The coefficient is positive, significant at the one percent level, and close to the baseline annual estimate. The main finding therefore holds under a different set of identifying assumptions.

6. Alternative Weighting Schemes

The baseline weights all firm-year observations equally, giving disproportionate influence to small firms that patent infrequently. If the process-innovation response differs by research intensity, the unweighted estimate may not represent the average effect across the distribution of innovative activity. I therefore re-estimate the specification using alternative firm-level weights that shift influence toward larger or more research-intensive firms.

Table A6 reports the results. Weighting by citation counts, R&D expenditure, and patent counts each yields a coefficient that is positive and significant, in line with the unweighted baseline. The result, therefore, is not sensitive to how firms are weighted.

VI. Conclusion

In this paper, I examine how Chinese import competition affects the type of innovation that U.S. manufacturing firms pursue. Using an instrumental variable strategy that exploits variation in Chinese import penetration to other high-income countries, I find that rising import competition induces firms to shift their innovative effort toward process innovation, which focuses on cost reduction rather than on new product development. This shift is economically meaningful. Importantly, this shift reflects a disproportionate increase in process-oriented inventive activity rather than a mechanical consequence of reduced product innovation, as both process and product patenting increase in response to import competition but the growth in process claims is substantially larger.

I also identify the conditions that shape this response. The shift toward process innovation is concentrated in high-product-similarity industries where differentiation is difficult, and it is further amplified among focused single-scope firms that cannot easily pivot to alternative business lines. The shift is also more pronounced for firms facing greater ex-ante uncertainty, as measured by cash-flow volatility and by total, idiosyncratic, and unlevered return volatility, which is consistent with process innovation offering safer and more predictable returns when overall business risk is already elevated.

Labor-intensive firms, for which labor constitutes a larger share of production costs and the return to cost-reducing innovation is therefore higher, similarly exhibit a stronger process shift. In contrast, firms that already possess alternative cost-reduction channels, namely vertically integrated firms and firms that already source inputs from China, show a weaker response because they can achieve cost savings through organizational or sourcing strategies rather than through internal innovation.

I further show that process innovation helps firms absorb the adverse effects of import competition. Firms with a higher process share experience smaller declines in profitability and in the medium-run growth of sales, assets, gross profit, employment, and capital when import penetration rises. Consistent with these real effects, the stock market rewards process-oriented patents for firms in high-product-similarity industries facing greater import competition, which are precisely the settings where process innovation is most strategically relevant. The market-based evidence complements the performance results by indicating that the reallocation toward process innovation reflects a value-relevant strategic response rather than a mechanical reaction to competitive pressure.

These findings are robust to pre-trend falsification, industry-level estimation, dynamic selection bounds, an alternative stacked first-difference specification, the exclusion of potentially confounding sectors, and alternative weighting schemes.

Taken together, the results in this paper highlight that the composition of innovation, and not only its level, is a meaningful margin through which firms adjust to foreign competitive shocks. Product market structure and firm characteristics play a central role in shaping this response, and the reallocation has measurable consequences for firm performance and market valuation. More broadly, the results suggest that understanding how firms respond to trade shocks requires looking beyond aggregate innovation activity to the strategic direction of that activity, which depends on the competitive environment firms face and the organizational resources available to them.

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Figure 1
Chinese Exports by Year

This figure plots the total trade value of Chinese exports to nine different high-income countries from 1996 to 2020. Each country is represented by a distinct line style and marker. Panel A plots exports to each country separately; the United States is consistently the largest importer of Chinese goods, starting around 50 billion USD in 1996, showing steep and consistent growth to peak around 570 billion USD in 2017, with a sharp dip in 2009 to about 280 billion USD during the global financial crisis, and a surge to approximately 450 billion USD by 2020. Japan and Germany represent the next largest importers, with Japan starting around 40 billion USD in 1996, peaking around 180 billion USD in 2011, and ending around 160 billion USD by 2020. Germany starts around 20 billion USD in 1996, peaks around 150 billion USD in 2011, and ends around 140 billion USD by 2020. All countries show a general upward trend from 1996 until the late 2000s, with a noticeable dip around 2009 consistent with the global financial crisis, followed by recovery and continued growth. The figure illustrates the dominance of the United States as a destination for Chinese exports and the strong positive correlation in export trends across countries, which supports the instrumental variable approach. Panel B plots the sum of imports by eight other high-income countries versus the United States.

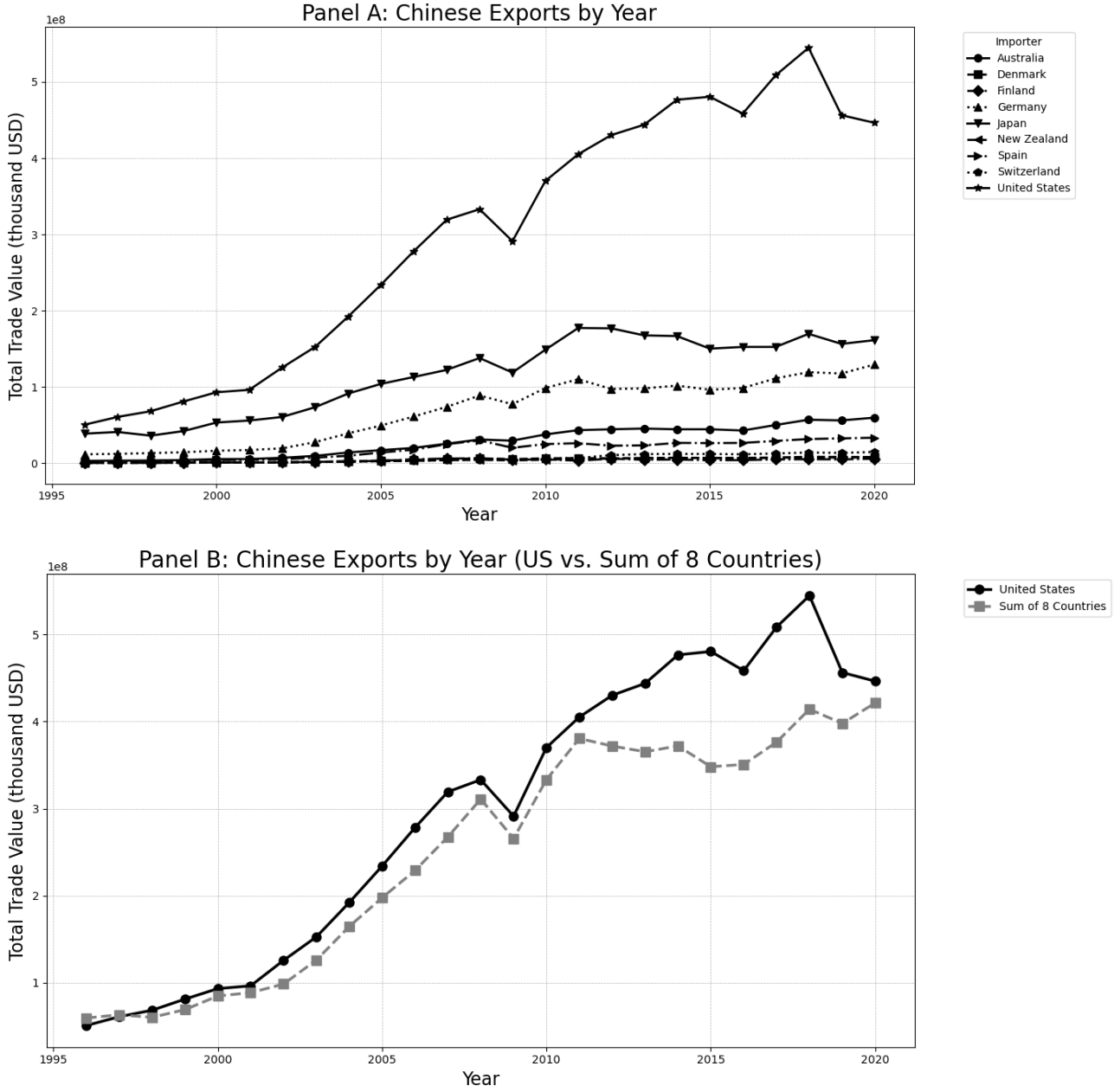


Figure 2
Chinese Import Penetration by Broad Manufacturing Industry

This figure presents twelve line charts, each displaying Chinese import penetration (in thousands of 2020 dollars per worker) from 1996 to 2020 for a broad manufacturing industry. The solid line is import penetration to the United States; the dashed line is import penetration to the eight other high-income countries used as the instrument. The twelve industries are: Food (SIC 20), Paper Products (SIC 26), Transportation Equipment (SIC 37), Chemical Products (SIC 28), Primary Metals (SIC 33), Rubber and Plastic Products (SIC 30), Lumber and Wood Products (SIC 24), Apparel (SIC 23), Electronic Equipment (SIC 36), Tobacco (SIC 21), Leather Products (SIC 31), and Industrial Machinery (SIC 35). Across most industries, both series show a general upward trend in Chinese import penetration from 1996 through a peak between roughly 2008 and 2012, followed by a decline or stabilization through 2020. The U.S. and other-country series tend to move in parallel, consistent with a common supply-side driver of Chinese export growth. The absolute level of import penetration varies widely across industries, from low tens of thousands of dollars per worker in Food and Tobacco to over a million dollars per worker in Apparel, Leather Products, and Electronic Equipment, illustrating the cross-sectional variation in import exposure exploited in the empirical analysis.

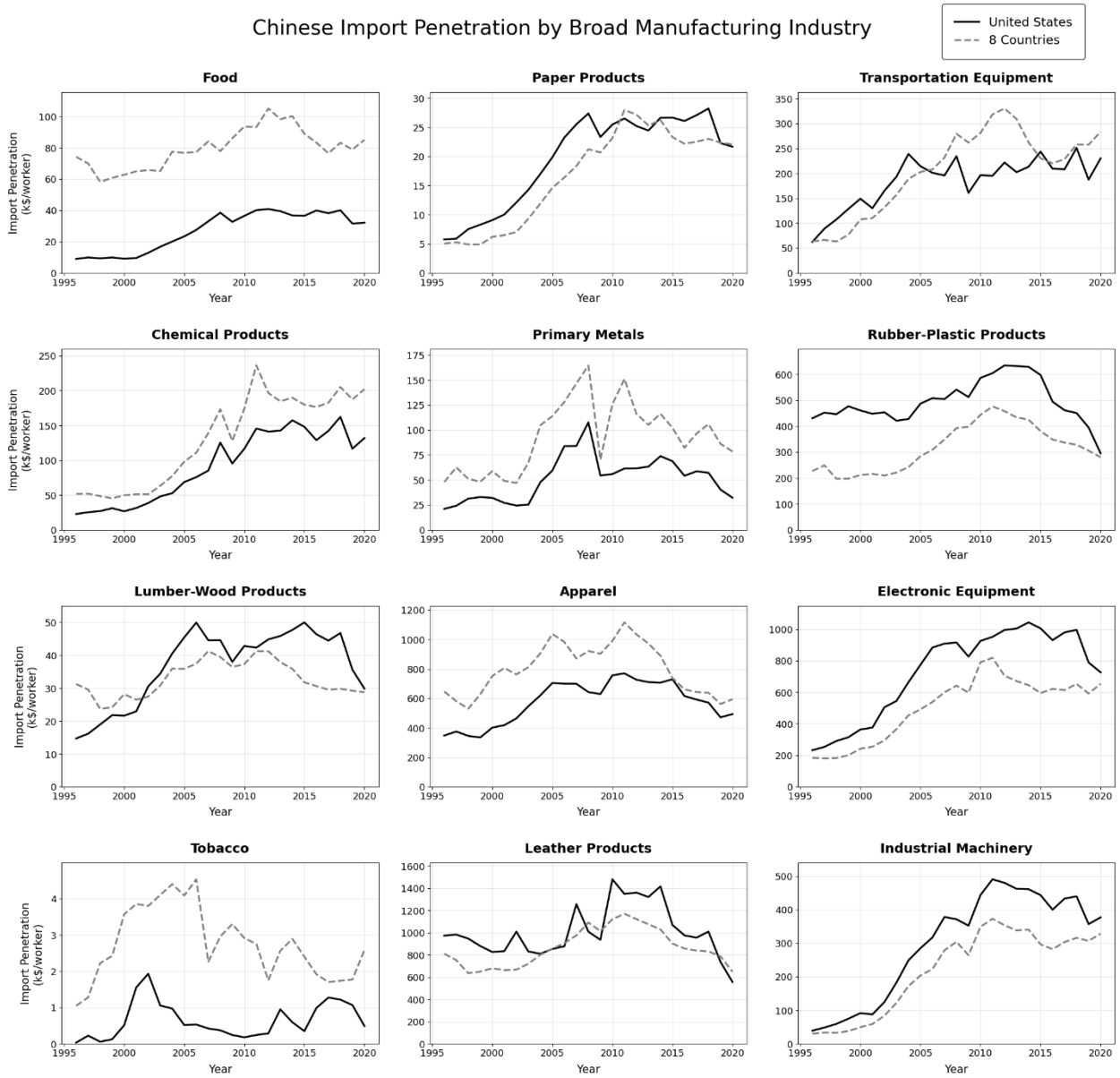


Figure 3
Process Innovation by Product Similarity

This figure plots the average share of process patents for U.S. manufacturing firms from 1996 to 2020, separately for High Sim firms, Low Sim firms, and the full sample. The solid black line represents firms with high product similarity, the dash-dotted line represents the full sample average, and the dashed line represents firms with low product similarity. High Sim is an indicator equal to one if the firm operates in a three-digit SIC industry with above-median product similarity in a given year and zero otherwise, where industry product similarity is constructed from the Hoberg and Phillips (2016) text-based similarity data as the average pairwise similarity across firms in the industry. The figure illustrates that firms with high product similarity consistently exhibit a higher average process share than the full sample, which in turn has a higher average process share than firms with low product similarity throughout the entire 25-year period. The gap between high-similarity and low-similarity firms appears to widen over time, particularly after the early 2000s, suggesting a growing divergence in innovation strategies based on product similarity.

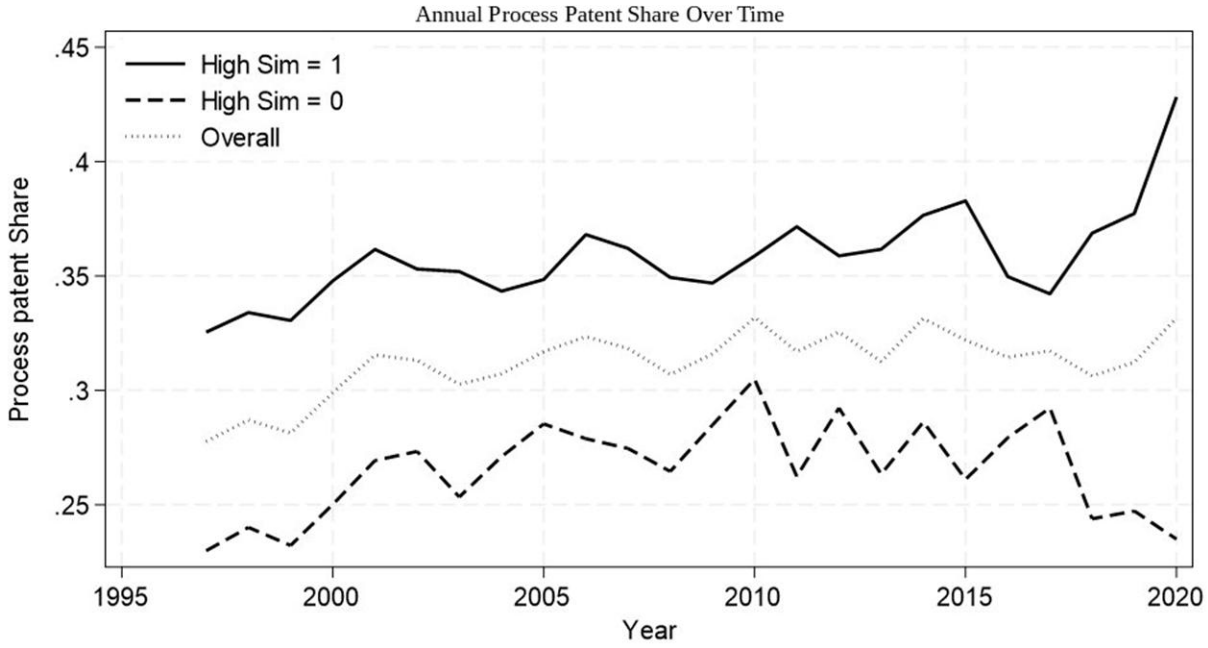


Figure 4
Change in Chinese Import Penetration

This figure presents a scatter plot of the change in Chinese import penetration in eight high-income countries (x-axis) against the change in Chinese import penetration in the United States (y-axis), both measured in thousands of dollars per worker. The plot displays numerous data points as small gray circles, showing the relationship between changes in import penetration across these regions. The red dashed line represents the linear trend fitted to the data. This line passes through the origin and has a positive slope of 1.06, suggesting that changes in Chinese import penetration in other eight high-income countries are strongly and positively associated with changes in Chinese import penetration in the United States. The figure provides visual evidence for the relevance condition of the instrumental variable, demonstrating that Chinese export growth to other developed economies is highly correlated with export growth to the U.S., consistent with common supply-side shocks driving Chinese exports across multiple markets.

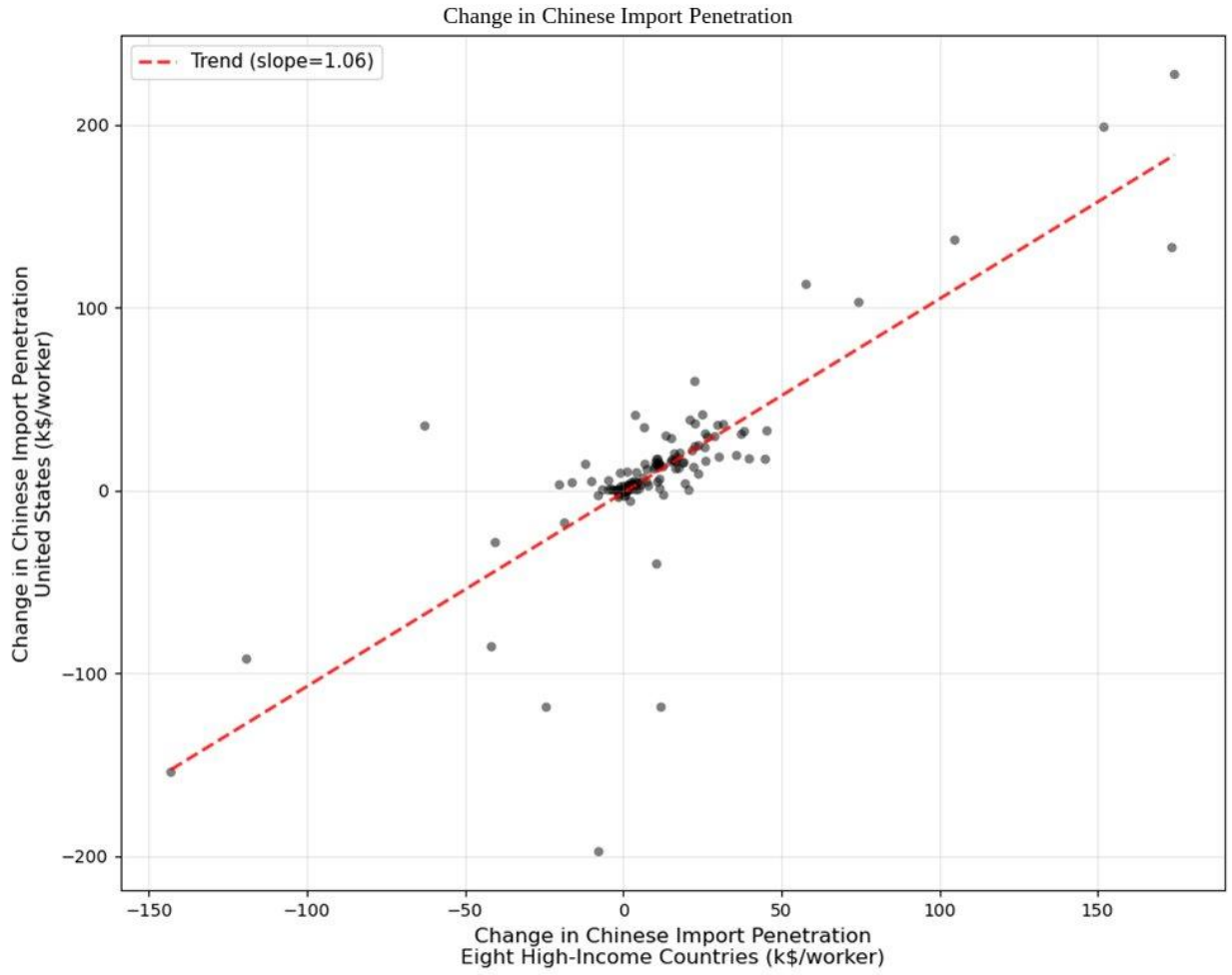


Table 1
Univariate Summary Statistics

This table reports univariate summary statistics for U.S. manufacturing firm-year observations from 1996–2020 used in the main analysis. It reports means and standard deviations for the full sample and separately for firms in high- and low-product-similarity industries. High (Low) Sim is an indicator equal to one if the firm operates in a three-digit SIC industry with above-median (below-median) product similarity in a given year and zero otherwise, where industry product similarity is constructed from the Hoberg and Phillips (2016) text-based similarity data as the average pairwise similarity across firms in the industry. Product similarity is unavailable for some observations, so the high- and low-similarity subsamples do not sum to the full sample. Process Share is the fraction of a firm's patents filed in a given year whose first (primary) claim is classified as a process claim; Import Penetration (IP) is industry-level Chinese import penetration (2020 dollars normalized by base-year industry employment). The last two columns report High–Low differences and t-statistics for the differences. All continuous variables are winsorized at the 1st/99th percentiles; variable definitions are in Appendix A, and ***, **, * denote 1%, 5%, and 10% significance.

N =	Full sample 19,720		High Sim 12,693		Low Sim 6,850		Diff (High-Low)	t-stats
Variable	Mean	SD	Mean	SD	Mean	SD		
Process Share	0.322	0.318	0.354	0.322	0.265	0.302	0.089***	18.81
IP ($K/Worker)	36.058	70.225	35.138	69.014	37.887	72.936	-1.314	-1.21
Log (Total Assets)	6.921	2.226	6.796	2.308	7.108	2.037	-0.293***	-8.80
R&D/Total Sales	1.138	5.613	1.679	6.843	0.165	1.547	1.454***	18.02
Log (firm age)	2.625	0.919	2.491	0.910	2.864	0.883	-0.342***	-28.03
Market to Book	2.122	1.883	2.393	2.072	1.646	1.361	0.699***	25.56

Table 2
The Effect of Chinese Import Competition on Process Innovation

The table reports 2SLS regressions relating firms' process innovation to Chinese import penetration (IP). Column (1) reports the first stage, in which U.S. firm-level Chinese import penetration is regressed on Chinese import penetration in eight other high-income countries (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland) with the controls and fixed effects listed below. Columns (3) and (5) report second-stage estimates for two measures of process innovation as the dependent variable, while columns (2) and (4) report OLS results. The dependent variables under the Process Share column are defined as the fraction of a firm's patents filed in a given year whose first (primary) claim is classified as a process claim. Under the Process Claims Share column, the dependent variables are defined as the share of the number of process claims over the number of total claims across all patents the firm files that year. IP is instrumented using the eight-country instrument described above. The control variables are Log (Total Assets), R&D/Total Sales, Log (Firm Age), and Market-to-Book. All specifications include firm and year fixed effects. Standard errors are clustered at the three-digit SIC industry level and are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are in Appendix A.

		Process Share		Process Claims Share	
	First-Stage	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)
IP in other high-income	0.8990***				
	(0.053)				
IP		0.0183***	0.0199***	0.0139***	0.0168***
		(0.0039)	(0.0039)	(0.0032)	(0.0038)
Log (Total Assets)	0.0019	0.0001	0.0001	-0.0047	-0.0046
	(0.0084)	(0.0045)	(0.0045)	(0.0040)	(0.0045)
R&D/Total Sales	-0.0002	-0.0011***	-0.0011***	-0.0010***	-0.0010**
	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0004)
Log (firm age)	-0.0108	0.0126	0.0125	0.0117	0.0114
	(0.0161)	(0.0095)	(0.0095)	(0.0115)	(0.0115)
Market to Book	0.0001	0.0010	0.0010	0.0020	0.0021
	(0.0036)	(0.0014)	(0.0014)	(0.0016)	(0.0016)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	19,720	19,720	19,720	19,720	19,720
R^2	0.974	0.378		0.372	

Table 3
The Effect of Chinese Import Competition on Patent and Claim Counts

The table reports IV regressions relating firms' patenting activity and the composition of their innovation to Chinese import penetration (Instrumented IP). Each dependent variable is measured at the firm-year level using patent filing dates. In column (1) the dependent variable is the log of one plus the number of patents the firm files that year. In column (2) the dependent variable is the log of one plus the firm's total number of patent claims. In column (3) the dependent variable is the log of one plus the number of process claims. In column (4) the dependent variable is the log of one plus the number of product claims. In column (5) the dependent variable is the log of the ratio of process to product claims, computed as log of (1 + process claims) divided by (1 + product claims) so the measure is defined when a firm files no product claims. A positive coefficient in columns (3) and (5) indicates that process claims rise, and rise faster than product claims, as import competition increases. Instrumented IP is U.S. firm-level Chinese import penetration, instrumented using Chinese import penetration in eight other high-income countries (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland). The control variables are Log (Total Assets), R&D/Total Sales, Log (Firm Age), and Market-to-Book. All specifications include firm and year fixed effects. Standard errors are clustered at the three-digit SIC industry level and are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are in Appendix A.

Dependent variable is log one plus	patents	All claims	process claims	product claims	process/product
	(1)	(2)	(3)	(4)	(5)
Instrumented IP	0.0583**	0.0686**	0.0874***	0.0477*	0.0396**
	(0.0231)	(0.0279)	(0.0291)	(0.0259)	(0.0153)
Log (Total Assets)	0.2778***	0.2899***	0.2612***	0.2954***	-0.0342**
	(0.0495)	(0.0511)	(0.0530)	(0.0498)	(0.0139)
R&D/Total Sales	-0.0021**	-0.0022*	-0.0031*	-0.0004	-0.0028**
	(0.0009)	(0.0013)	(0.0018)	(0.0007)	(0.0012)
Log (firm age)	0.0522	0.0088	0.0428	0.0027	0.0401
	(0.0332)	(0.0382)	(0.0438)	(0.0379)	(0.0411)
Market to Book	0.0332***	0.0408***	0.0435***	0.0334***	0.0101
	(0.0070)	(0.0075)	(0.0092)	(0.0078)	(0.0083)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	19,720	19,720	19,720	19,720	19,720
Within R^2	0.0498	0.0363	0.0296	0.0333	0.0017

Table 4

The Effect of Chinese Import Competition on Process Innovation: Product Similarity and Focused Firms

The table reports IV regressions relating firms' process innovation to Chinese import penetration (IP) and its interaction with product similarity and firm scope. The dependent variable is Process Share, the fraction of a firm's patents in a given year whose first (primary) claim is classified as a process claim. High Sim is an indicator equal to one if the firm operates in a three-digit SIC industry with above-median product similarity in a given year and zero otherwise, where industry product similarity is constructed from the Hoberg and Phillips (2016) text-based similarity data as the average pairwise similarity across firms in the industry. Focused Firm is an indicator equal to one if the firm operates in only a single product market and zero otherwise, based on the Hoberg and Phillips (2025) 10-K-based product-market scope measure. Column (1) interacts IP with High Sim to test whether the process-innovation response is stronger in high-similarity industries. Column (2) interacts IP with Focused Firm to test whether the response differs for single-market firms. Column (3) adds the triple interaction IP × High Sim × Focused Firm to test whether the process shift is strongest for firms that are both in high-similarity industries and operate in a single market. IP and all interaction terms with IP are instrumented using Chinese import penetration in eight other high-income countries (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland). The control variables are Log (Total Assets), R&D/Total Sales, Log (Firm Age), and Market-to-Book. All specifications include firm and year fixed effects. Standard errors are clustered at the three-digit SIC industry level and are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are in Appendix A.

Dependent variable is	Process Share	Process Share	Process Share
	High Sim	Focused Firm	High Sim × Focused Firm
	(1)	(2)	(3)
Instrumented IP	0.0080	0.0234***	0.0130*
	(0.0058)	(0.0063)	(0.0068)
High Sim	-0.0069		-0.0003
	(0.0110)		(0.0113)
IP × High Sim	0.0167***		0.0147**
	(0.0060)		(0.0059)
Focused Firm		0.0109	0.0154
		(0.0151)	(0.0213)
Instrumented IP × Focused Firm		-0.0101	-0.0325***
		(0.0188)	(0.0114)
High Sim × Focused Firm			-0.0093
			(0.0246)
Instrumented IP × High Sim × Focused Firm			0.0378**
			(0.0177)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	19,543	17,432	17,339
Within R^2	0.0018	0.0018	0.0024

Table 5
The Effect of Chinese Import Competition on Process Innovation: Ex-Ante Risk

The table reports IV regressions relating firms' process innovation to Chinese import penetration (IP) and firm-level risk. The dependent variable is Process Share, defined as the fraction of a firm's patents in a given year whose first (primary) claim is classified as a process claim. Risk is an indicator equal to one if the corresponding risk measure is above the annual sample median and zero otherwise. Cash-flow volatility (column 1) is the standard deviation of operating cash flow scaled by total assets over the preceding five fiscal years. Total return volatility (column 2) is the standard deviation of the firm's daily stock returns over the fiscal year. Idiosyncratic volatility (column 3) is the standard deviation of the residuals from a market model estimated over the fiscal year. Unlevered volatility (column 4) is total return volatility scaled by the ratio of the market value of equity to the market value of assets, isolating business risk from leverage. Each specification includes the interaction between IP and Risk to test whether the effect of import competition on process innovation is stronger for high-risk firms. IP and all interaction terms with IP are instrumented using Chinese import penetration in eight other high-income countries (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland). The control variables are Log (Total Assets), R&D/Total Sales, Log (Firm Age), and Market-to-Book. All specifications include firm and year fixed effects. Standard errors are clustered at the three-digit SIC industry level and are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are in Appendix A.

Dependent variable is	Process Share	Process Share	Process Share	Process Share
Risk Measure is	CF Vol	Total Vol	Idio Vol	Unlevered Vol
	(1)	(2)	(3)	(4)
Instrumented IP	0.0153***	0.0150***	0.0151***	0.0132***
	(0.0039)	(0.0042)	(0.0056)	(0.0042)
Risk	0.0041	-0.0042	-0.0102	-0.0106
	(0.0055)	(0.0086)	(0.0068)	(0.0075)
Instrumented IP × Risk	0.0110***	0.0090**	0.0086*	0.0119***
	(0.0041)	(0.0040)	(0.0050)	(0.0036)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	18,668	19,677	19,677	19,676
Within R^2	0.0018	0.0015	0.0015	0.0015

Table 6
The Effect of Chinese Import Competition on Process Innovation: Labor Intensity

The table reports IV regressions examining whether the effect of Chinese import penetration on firms' process innovation is stronger in labor-intensive industries over 1996–2020. The dependent variable is Process Share, defined as the fraction of a firm's patents in a given year whose first (primary) claim is classified as a process claim. Industry labor intensity is measured two ways. In column (1) it is industry employment divided by industry value added, where value added is the BEA measure of an industry's gross output net of its purchased intermediate inputs, so the ratio captures labor used per dollar of value the industry itself generates; higher values indicate that labor accounts for a larger share of production relative to output, using data from the BEA Industry Economic Accounts following Palacios (2013). In column (2) it is industry employment divided by the aggregate stock of property, plant, and equipment (PPE), capturing labor relative to physical capital, using Compustat data aggregated to the three-digit SIC level. Labor Int. is an indicator equal to one if the corresponding labor-intensity measure is above the annual sample median and zero otherwise. Each specification includes the interaction between import penetration (IP) and Labor Int. to test whether the process-innovation response is stronger for labor-intensive firms. IP and all interaction terms with IP are instrumented using Chinese import penetration in eight other high-income countries (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland). The control variables are Log (Total Assets), R&D/Total Sales, Log (Firm Age), and Market-to-Book. All specifications include firm and year fixed effects. Standard errors are clustered at the three-digit SIC industry level and are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are in Appendix A.

Dependent variable is	Process Share	Process Share
Labor intensity measure is	Emp/Value Added	Emp/PPE
	(1)	(2)
Instrumented IP	0.0111**	0.0141***
	(0.0050)	(0.0052)
Labor Int.	-0.0111	0.0004
	(0.0135)	(0.0121)
Instrumented IP × Labor Int.	0.0123**	0.0101*
	(0.0059)	(0.0058)
Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	16,124	19,450
Within R^2	0.0015	0.0016

Table 7

The Effect of Chinese Import Competition on Process Innovation: Cost-Reduction Substitutes

The table reports IV regressions relating firms' process innovation to Chinese import penetration (IP) and firms' access to alternative cost-reduction channels. The dependent variable is Process Share, defined as the fraction of a firm's patents in a given year whose first (primary) claim is classified as a process claim. In column (1) the dummy is Vertically Integrated. Vertically Integrated is an indicator equal to one if the firm's vertical integration score is above the annual sample median and zero otherwise, where the score is constructed from 10-K text analysis following Frésard, Hoberg, and Phillips (2020) and captures the degree to which the firm's operations span multiple stages of production within the firm boundary. In column (2) the dummy is Input from China. Input from China is an indicator equal to one if the firm discloses in its 10-K filings that it sources production inputs, components, or materials from China and zero otherwise, following Hoberg and Moon (2017). Each specification includes the interaction between IP and the corresponding dummy to test whether the process-innovation response is weaker for firms that already have these cost-reduction channels. IP and all interaction terms with IP are instrumented using Chinese import penetration in eight other high-income countries (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland). The control variables are Log (Total Assets), R&D/Total Sales, Log (Firm Age), and Market-to-Book. All specifications include firm and year fixed effects. Standard errors are clustered at the three-digit SIC industry level and are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are in Appendix A.

Dependent variable is	Process Share	Process Share
Dummy variable is	Vertically Integrated	Input from China
	(1)	(2)
Instrumented IP	0.0287***	0.0296***
	(0.0071)	(0.0054)
Dummy	0.0165	0.0142
	(0.0108)	(0.0100)
Instrumented IP × Dummy	-0.0151**	-0.0099*
	(0.0064)	(0.0059)
Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	17,412	14,750
Within R^2	0.002	0.0019

Table 8
The Effect of Process Innovation on Firm Performance

The table reports regressions relating firm performance to Chinese import penetration (IP) and process innovation. In column (1) the dependent variable is ROA, operating income before depreciation over total assets, measured in year t. In columns (2) through (6) the dependent variable is the medium-run log change in a firm outcome from year t to t+3: sales growth (column 2), asset growth (column 3), gross profit growth (column 4), employee growth (column 5), and net PPE growth (column 6), each computed as the log of the year t+3 value minus the log of the year t value. Process Share is the fraction of a firm's patents filed in a given year whose first (primary) claim is classified as a process claim. Each specification includes IP, Process Share, and their interaction IP × Process Share, the coefficient of interest, which captures whether a higher process share buffers firm performance against import competition. IP and all interaction terms with IP are instrumented using Chinese import penetration in eight other high-income countries (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland). The control variables are Log (Total Assets), R&D/Total Sales, Log (Firm Age), and Market-to-Book. All specifications include firm and year fixed effects. Standard errors are clustered at the three-digit SIC industry level and are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are in Appendix A.

Dependent variable is	ROA	Sales Growth (t to t+3)	Asset Growth (t to t+3)	GP Growth (t to t+3)	Emp. Growth (t to t+3)	PPE Growth (t to t+3)
	(1)	(2)	(3)	(4)	(5)	(6)
Instrumented IP	-0.0069*	-0.0579*	-0.0609**	-0.0500*	-0.0380*	-0.0388*
	(0.0037)	(0.0324)	(0.0280)	(0.0266)	(0.0197)	(0.0221)
Process Share	0.0024	-0.0021	-0.0390**	-0.0273	-0.0238	-0.0406*
	(0.0069)	(0.0152)	(0.0194)	(0.0233)	(0.0149)	(0.0238)
Instrumented IP × Process Share	0.0084**	0.0270***	0.0361***	0.0222*	0.0372***	0.0501**
	(0.0036)	(0.0096)	(0.0127)	(0.0115)	(0.0122)	(0.0199)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,512	17,135	17,135	15,340	16,813	17,103
Within R^2	0.0385	0.1077	0.1814	0.0967	0.0913	0.0959

Table 9
Process Innovation and Cumulative Abnormal Returns

The table reports regressions relating cumulative abnormal returns around patent grant dates to process innovation and Chinese import penetration (IP). The dependent variable in all columns is CAR [−1,+1], the three-day cumulative abnormal return over the window from one trading day before to one trading day after the patent grant date, computed from a market model estimated on a 253-day window ending 63 days before the grant. Process Share is the fraction of a firm's patents filed in a given year whose first (primary) claim is classified as a process claim. High Sim is an indicator equal to one if the firm operates in a three-digit SIC industry with above-median product similarity in a given year and zero otherwise, where industry product similarity is constructed from the Hoberg and Phillips (2016) text-based similarity data as the average pairwise similarity across firms in the industry. Column (1) includes Process Share alone. Column (2) adds IP and the interaction Process Share × IP, testing whether the market's valuation of process innovation varies with import competition. Column (3) adds the triple interaction Process Share × IP × High Sim, testing whether the market response is strongest for process innovation in high-similarity industries facing import competition. IP and all interaction terms with IP are instrumented using Chinese import penetration in eight other high-income countries (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland). The control variables are Log (Total Assets), R&D/Total Sales, Log (Firm Age), and Market-to-Book. All specifications include industry and year fixed effects. Standard errors are clustered at the three-digit SIC industry level and are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are in Appendix A.

Dependent variable is	CAR [-1,+1] (1)	CAR [-1,+1] (2)	CAR [-1,+1] (3)
Process Share	0.179*	0.198	0.382*
	(0.104)	(0.123)	(0.214)
Instrumented IP		0.002	0.001
		(0.003)	(0.004)
Process Share × Instrumented IP		-0.001	-0.003**
		(0.001)	(0.001)
High Sim			-0.628
			(0.391)
Process Share × High Sim			-0.252
			(0.259)
IP × High Sim			0.001
			(0.002)
Process Share × Instrumented IP × High Sim			0.004***
			(0.001)
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	1,204,540	1,164,788	1,119,144
Within R^2	0.0009	0.0008	0.0008

Foreign Import Competition and Process Innovation

Appendix

A. Variable Definitions

1. Import Competition Variables

Import Penetration (IP). Industry-level Chinese import penetration, measured as Chinese imports to a given destination country in 2020 U.S. dollars divided by U.S. manufacturing employment in a fixed base year (1999) at the three-digit SIC industry level. The measure is constructed for the United States (used as the endogenous variable) and for eight other high-income countries, namely Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland (used to construct the instrument). Using U.S. base-year employment as the denominator for both the endogenous variable and the instrument ensures that the two variables differ only in the source of the trade flow rather than in how exposure is normalized. Chinese import data are obtained from the BACI international trade database (Gaulier and Zignago 2010), which provides harmonized bilateral trade flows at the HS96 product level. Imports are aggregated from HS96 product codes to three-digit SIC industries using the concordance tables provided by David Dorn on his website. U.S. industry employment is obtained from the County Business Patterns (CBP) database.

2. Innovation Variables

Process Share. The main measure of innovation type, constructed from the claim-level patent classifications developed by Ganglmair, Robinson, and Seeligson (2022), who classify each independent claim in a U.S. patent as either a process claim or a product claim based on the preamble and body of the claim. A process claim describes a method, procedure, or sequence of steps used to produce or transform something, while a product claim describes a composition, machine, article of manufacture, or other tangible output. Patents follow a hierarchical structure in which the first claim defines the primary invention, with subsequent claims typically describing variants or dependent features. Following Bena and Simintzi (2025), a patent is classified as a

process patent if its first (primary) claim is a process claim. Process Share is defined as the fraction of a firm's patents filed in a given year whose first claim is a process claim. Patent filing dates rather than grant dates are used to align the measure with the timing of innovation decisions.

Process Claims Share (Alternative Measure). An alternative measure of process innovation defined as the total number of process claims across all patents filed by the firm in a given year, divided by the total number of claims across the same set of patents. This measure captures the intensity of process orientation within the firm's patent portfolio rather than classifying patents based only on their primary claim, and it serves as a robustness check on the main Process Share variable.

Log(1 + Patents). The natural logarithm of one plus the number of patents filed by the firm in a given year, using filing dates.

Log(1 + Claims). The natural logarithm of one plus the total number of independent claims across all patents filed by the firm in a given year.

Log(1 + Process Claims). The natural logarithm of one plus the total number of process claims across the firm's patents in a given year, where process claims are identified using the Ganglmair, Robinson, and Seeligson (2022) classification.

Log(1 + Product Claims). The natural logarithm of one plus the total number of product claims across the firm's patents in a given year, defined analogously to process claims.

Log(Proc-to-Prod Claims). The natural logarithm of the ratio of process claims to product claims across all patents filed by the firm in a given year. To handle cases in which a firm files no product claims in a given year, the ratio is computed as (1 + process claims) / (1 + product claims), so that the variable is well defined for all firm-years with at least one patent.

3. Product Market Structure Variables

High Sim. An indicator variable equal to one if the firm's industry-level product similarity is above the annual median across the full sample, and zero otherwise. Product similarity is constructed from the TNIC-all data provided by Hoberg and Phillips (2016), which uses text-based analysis of 10-K product descriptions to compute pairwise similarity scores between firms. Industry-level similarity is the average pairwise similarity across all firms classified in the same three-digit SIC industry in a given year, with higher values indicating greater product overlap and thus more intense competitive pressure along the product dimension.

Focused Firm. An indicator equal to one if the firm operates in only a single product-market scope and zero otherwise, following Hoberg and Phillips (2025). Product-market scope is derived from the firm's 10-K product descriptions and reflects the breadth of distinct business lines in which the firm operates. Single-scope firms are focused firms with limited ability to reallocate activity across business segments when competitive pressure intensifies in their primary market.

4. Risk Measures

Cash Flow Volatility. Following Garfinkel and Hankins (2011), the standard deviation of the firm's operating cash flow scaled by total assets, computed over the preceding five fiscal years. A minimum of three non-missing annual observations is required for the measure to be computed.

Total Return Volatility. The standard deviation of the firm's daily stock returns over the fiscal year.

Idiosyncratic Volatility. The standard deviation of the daily residuals from a market model estimated over the fiscal year, where the market model regresses daily stock returns on the value-weighted CRSP market return.

Unlevered Volatility. Total return volatility adjusted for financial leverage, computed as total return volatility multiplied by the ratio of the market value of equity to the market value of assets. This measure isolates the volatility of the firm's underlying business activity from the volatility induced by its capital structure.

Risk. For each of the four volatility measures above, an indicator equal to one if the corresponding measure is above the annual sample median and zero otherwise. This indicator is used in interaction tests to identify high-risk firms.

5. Labor Intensity Variables

Labor Intensity (Employees / Value Added). Following Palacios (2013), an industry-level measure of labor intensity defined as total industry employment divided by industry value added, computed at the three-digit SIC level. Employment and value-added data are obtained from the Bureau of Economic Analysis (BEA) Industry Economic Accounts. Higher values indicate that labor accounts for a larger share of production activity relative to the output it generates.

Labor Intensity (Employees / PPE). An alternative industry-level measure of labor intensity defined as total industry employment divided by the aggregate stock of property, plant, and equipment in the industry, computed using Compustat variables aggregated to the three-digit SIC level. This measure captures labor intensity relative to the firm's physical capital stock rather than to value added.

Labor Int. An indicator equal to one if the corresponding labor intensity measure is above the annual sample median and zero otherwise.

6. Cost-Reduction Substitute Variables

Vertically Integrated. Following Frésard, Hoberg, and Phillips (2020), an indicator equal to one if the firm's vertical integration score is above the annual sample median and zero otherwise. The

vertical integration score is constructed from 10-K text analysis and captures the degree to which a firm's operations span multiple stages of the production process within the same firm boundary, using input-output relationships between industries to identify vertical links. Higher scores indicate greater vertical integration and thus a greater ability to optimize costs internally through coordination across production stages.

Input from China. Following Hoberg and Moon (2017), an indicator equal to one if the firm discloses in its 10-K filings that it sources production inputs, components, or materials from China, and zero otherwise. The measure is constructed from text-based analysis of firms' 10-K disclosures and captures direct exposure to Chinese cost structures through supply-chain relationships rather than through competition in output markets.

7. Firm Performance Variables

Return on Assets (ROA). Operating income before depreciation (Compustat item OIBDP) divided by total assets (Compustat item AT), measured in the same fiscal year.

Sales Growth (0 to 3). The log change in firm sales between year t and year t+3, computed as log(Sales_{t+3}) minus log(Sales_t), where Sales corresponds to Compustat item SALE. This captures medium-run growth in firm revenue following the observation year.

Asset Growth (0 to 3). The log change in total assets between year t and year t+3, computed analogously to sales growth using Compustat item AT.

Gross Profit Growth (0 to 3). The log change in gross profit between year t and year t+3, where gross profit is defined as sales minus cost of goods sold (Compustat item SALE minus COGS).

Employee Growth (0 to 3). The log change in the number of employees between year t and year t+3, using Compustat item EMP.

PPE Growth (0 to 3). The log change in net property, plant, and equipment between year t and year t+3, using Compustat item PPENT.

8. Market Valuation Variable

CAR [−1, +1]. The cumulative abnormal stock return over the three-day window surrounding the patent grant date, including one trading day before the grant, the grant day itself, and one trading day after. Abnormal returns are computed using a market model in which daily stock returns are regressed on the value-weighted CRSP market return over an estimation window of 253 trading days ending 63 days before the grant date. A minimum of 100 trading days of non-missing return observations is required within the estimation window for the measure to be computed. The 63-day gap between the estimation window and the event window is used to avoid contamination of the estimation from pre-grant information leakage.

9. Control Variables

Log(Total Assets). The natural logarithm of total assets (Compustat item AT), measured in millions of U.S. dollars.

R&D / Total Sales. Research and development expenditures (Compustat item XRD) divided by total sales (Compustat item SALE). Missing values of XRD are set to zero following common practice in the innovation literature, under the assumption that firms not reporting R&D typically have negligible formal R&D activity.

Log(Firm Age). The natural logarithm of firm age, measured as the number of years since the firm first appeared in the Compustat database.

Market-to-Book. Following Frank and Goyal (2009), the ratio of the market value of assets to the book value of assets, where the market value of assets is defined as the book value of assets minus

the book value of equity plus the market value of equity. Higher values indicate higher market expectations about the firm's future profitability relative to its accounting value.

Table A1

The Effect of Chinese Import Competition on Process Innovation Excluding Computers Industry

The table reports the full set of coefficient estimates from the baseline IV regression of Process Share on Chinese import penetration, excluding the computer industry (SIC 357). Process Share is the fraction of a firm's patents in a given year whose first (primary) claim is classified as a process claim. IP is Chinese import penetration, instrumented using Chinese import penetration in eight other high-income countries (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland). The control variables are Log (Total Assets), R&D/Total Sales, Log (Firm Age), and Market-to-Book. All specifications include firm and year fixed effects. Standard errors are clustered at the three-digit SIC industry level and are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are in Appendix A.

Dependent Variable is	Process Share
	(1)
Instrumented IP	0.0127***
	(0.0046)
Log (Total Assets)	0.0028
	(0.0045)
R&D/Total Sales	-0.0012***
	(0.0003)
Log (firm age)	0.0107
	(0.0099)
Market to Book	0.0015
	(0.0013)
Firm FE	Yes
Year FE	Yes
Observations	18,531
$Within\ R^2$	0.03

Table A2
Pre-Trend Falsification Test

The dependent variable is the change in the industry-level, patent-weighted process share over the pre-period (1996 to 2001), where the process share is the ratio of process patents to total classified patents in an industry-year and a process patent is one whose first (primary) claim is classified as a process claim. The independent variable is the change in import penetration over the post-period. Columns (1) and (2) use the post-period 2001–2006; columns (3) and (4) use 2001–2020. Columns (1) and (3) estimate by OLS; columns (2) and (4) instrument the change in U.S. import penetration with the corresponding change in import penetration in eight other high-income countries (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland). The data are collapsed to the three-digit SIC industry level. An insignificant coefficient indicates that the process share was not trending differentially in industries that would later experience greater Chinese import competition. Robust standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are in Appendix A.

Dependent Variable is	Δ Process Share (1996–2001)			
	OLS	IV	OLS	IV
Post-period	2001–2006	2001–2006	2001–2020	2001–2020
	(1)	(2)	(3)	(4)
Δ Import Penetration (post)	0.0002	0.0002	0.0002	0.0002
	(0.0003)	(0.0003)	(0.0002)	(0.0002)
Observations	90	90	44	44
Within R^2	0.002	0.002	0.016	0.015

Table A3

The Effect of Chinese Import Competition on Process Innovation: Industry-Level Estimates

The table reports IV regressions of Process Share on Chinese import penetration at the industry level. The data are collapsed to the three-digit SIC industry-by-year level, where the industry process share is the ratio of process patents to total classified patents in an industry-year and a process patent is one whose first (primary) claim is classified as a process claim. In column (1) the dependent variable is the patent-weighted process share, which weights each industry-year by its number of patents so that industries with more innovative activity carry more weight; in column (2) it is the unweighted process share, which treats each industry-year equally. IP is Chinese import penetration, instrumented using Chinese import penetration in eight other high-income countries (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland). Import penetration is standardized by the firm-level standard deviation for comparability with the firm-level estimates. The control variables are Log (Total Assets), R&D/Total Sales, Log (Firm Age), and Market-to-Book. All specifications include industry and year fixed effects. Standard errors are clustered at the three-digit SIC industry level and are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are in Appendix A.

Dependent variable is	Process Share	Process Share
	Patent-weighted	unweighted
	(1)	(2)
Instrumented IP	0.0282***	0.0213
	(0.0047)	(0.0205)
Controls	Yes	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes
Observations	2,202	2,202
Within R^2	0.107	0.010

Table A4
Dynamic Selection Bias Bounds

This table assesses the sensitivity of the main result to dynamic selection bias following Bloom, Draca, and Van Reenen (2016). The dependent variable is Process Share, the fraction of a firm's patents in a given year whose first (primary) claim is classified as a process claim. For each specification, pseudo observations are created for firms that exit the estimation sample before the end of the panel. Column (1) assigns exiting firms their last observed process share for all post-exit years. Column (2) assigns the industry-year mean process share among surviving firms. Column (3) restricts to firms that exit for at least three consecutive years. Column (4) restricts to firms that exit in the last five years of the sample. Column (5) reports the baseline estimate without pseudo observations. IP is instrumented using Chinese import penetration in eight other high-income countries (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland). All specifications include the same controls as the baseline (Log (Total Assets), R&D/Total Sales, Log (Firm Age), and Market-to-Book), firm and year fixed effects, and standard errors clustered at the three-digit SIC industry level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are in Appendix A.

Dependent variable is	Process Share				
Bound is	Last observed	Industry-year mean	Exit more than 3 consecutive years	Exit in the last 5 years	Baseline
	(1)	(2)	(3)	(4)	(5)
Instrumented IP	0.0136***	0.0251*	0.0138**	0.0155***	0.0199***
	(0.0029)	(0.0058)	(0.0058)	(0.0038)	(0.0039)
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	24,565	34,905	22,038	20,241	19,720

Table A5

Stacked First-Difference Estimates Following Autor, Dorn, and Hanson (2013)

The dependent variable is the change in Process Share, where Process Share is the fraction of a firm's patents in a given year whose first (primary) claim is classified as a process claim. The independent variable is the change in import penetration, standardized by the firm-level standard deviation. The panel is constructed by stacking four approximately six-year first differences (1996–2001, 2001–2007, 2007–2013, 2013–2019) at the firm level. The change in import penetration is instrumented using the corresponding change in import penetration in eight other high-income countries (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland). The control variables are start-of-period Log (Total Assets), R&D/Total Sales, Log (Firm Age), and Market-to-Book, plus period fixed effects. Standard errors are clustered at the three-digit SIC industry level and are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are in Appendix A.

Dependent Variable is	ΔProcess Share
	(1)
ΔIP	0.0153***
	(0.0054)
Log (Total Assets)	-0.0002
	(0.0029)
R&D/Total Sales	0.0002
	(0.0003)
Log (firm age)	-0.0103
	(0.0049)
Market to Book	-0.0022
	(0.0017)
Period FE	Yes
Observations	2,189
Within R^2	0.01

Table A6
Robustness to Alternative Weighting Schemes

The table reports IV regressions of Process Share on Chinese import penetration using alternative weighting schemes. Process Share is the fraction of a firm's patents in a given year whose first (primary) claim is classified as a process claim. Column (1) weights observations by citation counts (the log of one plus total citations received). Column (2) weights by R&D expenditure. Column (3) weights by patent counts (the log of one plus the number of patents). Column (4) reports the unweighted baseline. IP is Chinese import penetration, instrumented using Chinese import penetration in eight other high-income countries (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland). The control variables are Log (Total Assets), R&D/Total Sales, Log (Firm Age), and Market-to-Book. All specifications include firm and year fixed effects. Standard errors are clustered at the three-digit SIC industry level and are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are in Appendix A.

Dependent variable is Process Share under	Citation-weighted	R&D-weighted	Patent-weighted	Baseline
	(1)	(2)	(3)	(4)
Instrumented IP	0.0202**	0.0136**	0.0159***	0.0199***
	(0.0028)	(0.0049)	(0.0025)	(0.0038)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	19,720	18,534	18,207	19,720
Within R^2	0.0408	0.0350	0.0316	0.0301