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Abstract

We study how imported input price shocks affect both the intensity and direction of innovation. Using comprehensive French firm-level data combining accounting records, ownership structures, customs transactions and patents over the period 2014—2023, we construct firm-level exposure to input price shocks based on structural breaks in product-level import unit values from non-EU countries, aggregated using a shift-share design. Innovation intensity is measured using priority patent applications, while the direction of innovation is characterized by mapping patents to products and embedding them in a production network to distinguish innovations directly related to affected inputs from those connected through upstream, downstream, or technologically adjacent linkages. We find that input price shocks primarily affect the direction rather than the level of innovation. Exposed firms reallocate innovative activity toward connected technological domains, consistent with network-based directed technological change. This reallocation is strongest among firms at the technological frontier, while smaller and less productive firms adjust more through overall innovation intensity. We provide evidence for specific industries, showing that the shock-innovation impact-response is heterogeneous. We interpret our results as firms' resorting to what we label *defensive innovation*. Our findings can inform policy making and firm strategy in a context of increasing trade fragmentation and geopolitical risk.

Keywords: input trade shocks, directed innovation, trade fragmentation, patents
JEL codes: F14, O31, O33, F18

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1 Introduction

Prices occupy a central role in economic analysis. Beyond their importance for monetary policy, relative prices shape the incentives to innovate and can influence the direction of technological change. While the role of factor prices in directing innovation has been extensively studied, the effects of intermediate input prices have received comparatively less attention. Yet imported input prices may become an increasingly important determinant of technological trajectories in a context of rising trade fragmentation. Over the past decades, globalization and trade liberalization reduced trade costs and facilitated access to foreign intermediate inputs. However, rising geopolitical tensions, trade conflicts, export controls, economic sanctions, and supply-chain disruptions are increasingly constraining access to foreign inputs and potentially generating persistent increases in import prices. As economies have become deeply integrated into global value chains, these shocks propagate across production networks and affect a broad range of industries. Understanding how economies respond to imported-input price shocks is therefore essential for assessing the long-run consequences of trade fragmentation and to inform discussions on technological sovereignty and strategic autonomy. In the context of innovation, shocks may not only affect the *rate* of innovative activity, but also its *direction*, re-routing innovation toward technologies that reduce dependence on vulnerable foreign inputs. Given the path-dependent nature of technological change, these adjustments may have lasting implications for productivity growth, industrial competitiveness, and aggregate economic performance.

Economists have traditionally focused on the effects of positive input-supply shocks associated with globalization and trade liberalization on innovation. More recently, attention has turned to the consequences of negative shocks related to trade fragmentation, supply-chain disruptions, and geopolitical tensions, which have increased the cost and uncertainty of accessing foreign inputs. While existing studies suggest that such adverse shocks affect innovative activity, they primarily examine aggregate innovation outcomes and provide limited evidence on how they influence the allocation of innovative effort across technologies. Negative input supply shocks may discourage innovation by reducing profitability and increasing financing constraints. Conversely, they may induce technological adaptation by increasing incentives to develop input-saving technologies, substitute inputs, or innovations that reduce dependence on vulnerable foreign suppliers — strategies that we label *defensive innovation*. Whether trade fragmentation depresses innovation or redirects it toward greater technological autonomy remains largely unexplored.

In order to address this question, in this paper we investigate empirically the causal impact of imported-input price shocks on both the intensity and the direction of innovation at the firm level. By doing so, we build a bridge between the study of macroeconomic and microeconomic dynamics. Firm-level analysis offers two advantages over industry-level approaches. First, it isolates input-supply shocks from potentially confounding output trade shocks, which may be highly correlated at the industry level (Aghion et al., 2024). Second, it allows us to control for industry-specific trajectories through within-industry comparisons. Our analysis combines French administrative accounting records, ownership structures, customs transactions, and patent data over the period 2014–2023. Because innovation decisions are typically made at the business-group level, we aggregate affiliated entities and define the consolidated group as the unit of analysis. We construct firm-specific exposure to imported input price shocks using product-level trade data. Specifically, we identify structural breaks in import unit values for products imported into the EU from non-EU countries and aggregate these shocks using a shift-share design based on predetermined import shares. Innovation intensity is measured using priority patent applications. To characterize the direction of innovation, we map patents to products using the probabilistic concordance of Lybbert and Zolas (2014) and combine this information with the production network developed by Fetzer et al. (2024). This framework allows us to distinguish innovation related to products directly affected by shocks from innovation indirectly connected through upstream, downstream, or technologically adjacent domains.

Our results show that imported-input price shocks primarily affect the direction rather than the level of innovation. While exposure is associated with a modest increase in aggregate patenting, we find no evidence that firms increase innovation in technologies directly related to the affected inputs. Instead, firms significantly reallocate innovation toward technologies that are indirectly connected to affected products through production or technological linkages. This pattern is consistent with a form of network-based technological adaptation, whereby firms respond to input disruptions by innovating in related domains rather than directly within constrained input categories. We document substantial heterogeneity in these responses. Firms at the technological frontier exhibit stronger reallocation of innovation across related technological domains, while smaller and less productive firms display more pronounced changes in overall patenting intensity. Sectoral heterogeneity is also pronounced: highly regulated industries such as chemicals primarily redirect innovation toward adjacent technologies, pharmaceutical firms show weaker innovation responses, and strategically important sectors exhibit stronger within-domain innovation responses. Overall, these findings suggest that negative input supply shocks reshape not only the level of innovation but also its direction in a manner that depends on firms' capabilities and sectoral characteristics.

With this study, we provide three main contributions. First, we obtain firm-level evidence on how negative imported-input price shocks shape not only the intensity of innovation but also its direction. Our findings contribute to the literature on induced innovation and directed technical change by identifying mechanisms of defensive innovation, whereby adverse trade shocks stimulate firms to redirect inventive effort toward technologies that mitigate the exposure to higher input costs.

The second contribution is methodological: we develop a unified framework to measure the direction of innovation within production networks. Our approach combines a concordance between product and patent classifications with input-output linkages, allowing patent-level innovations to be mapped onto products and positioned within the production network. Whereas existing approaches typically measure directed innovation either within narrowly defined sectors exposed to a particular shock or across broad patent categories (e.g., green versus non-green technologies), our framework captures innovation responses throughout the economy, including technologically-related industries connected through production linkages. It therefore generalizes sector-specific measures of directed innovation while integrating recent advances in patent mapping and input-output network analysis.

Third, we contribute to the emerging literature on trade fragmentation, supply-chain risk, and geopolitical risk by constructing a novel firm-level measure of exposure to imported input price shocks. The measure exploits structural breaks in bilateral product-level import prices and aggregates them using a shift-share (Bartik-style) design, thereby isolating persistent increases in input costs from confounding demand- and export-side shocks. Using this measure, we show that firms facing adverse input-supply conditions systematically redirect innovation toward products connected to affected inputs, consistent with models of endogenous technological adjustment under trade fragmentation.

A further novelty of our analysis is that it moves beyond the dominating approach in the literature, which is to test the impact of single historical episodes such as China's accession to the World Trade Organization or export restrictions on rare earths and other critical materials. Instead, we provide a *systematic, multi-origin and multi-product* measure of global input disruptions. This broader perspective enables us to characterize firms' innovation responses to a wide range of supply-chain disruptions and to provide a comprehensive mapping of trade-induced input shocks.

Overall, our findings identify innovation as a key margin of adjustment to global fragmentation. Firms respond to adverse imported-input shocks not only by substituting suppliers or reorganizing production, but also by reorienting their technological trajectories to mitigate geopolitical and supply-chain risk.

The remainder of the paper is organized as follows. Section 2 reviews the literature. Section 3 presents the data, the construction of trade shocks and innovation measures, and the empirical strategy. Section 4 reports the main results and heterogeneity analyses. The last section concludes.

2 Literature review

A substantial economic literature studies the relationship between international trade and innovation (see Akcigit and Melitz, 2022 and Melitz and Redding (2021) for two general overviews). Early contributions study trade liberalization episodes and finds that reductions in input tariffs and improved access to foreign intermediates are associated with higher productivity, increased R&D expenditures, and greater patenting activity in developing economies. These contributions emphasize the role of imported intermediates and capital goods in fostering technological upgrading in developing economies where access to advanced foreign inputs facilitates catching-up and productivity growth (Amiti and Konings, 2007, Goldberg et al., 2010, Halpern et al., 2015). Related studies document gains in product innovation, quality upgrading, and export performance (Bas and Strauss-Kahn, 2015, Bas and Berthou, 2017, Bas and Paunov, 2021, Fieler et al., 2018). While some papers report more limited effects (Teshima, 2009), the consensus broadly supports the view that trade-induced reductions in input costs tend to improve firm performance and innovation.

This line of analysis has increasingly focused on the role of an easier or cheaper access to foreign intermediate inputs sourced by advanced economies from low-wage countries, particularly following the "China shock" — China's accession to the World Trade Organization in 2001. This body of work delivers mixed evidence on the innovation effects of globalization. Bloom et al. (2016) find that exposure to Chinese import competition is associated with increased patenting in Europe, while Autor et al. (2020a) document a decline in innovation and patenting among U.S.firms facing stronger Chinese import competition. This divergence underscores the importance of distinguishing between input-supply effects and demand-side competitive pressures, a distinction formalized in more recent work such as Aghion et al. (2024), who separately identify negative demand shocks (import competition) and positive supply shocks (access to cheaper inputs). Their results suggest that while competition tends to depress innovation, improved access to foreign inputs generates more nuanced and heterogeneous responses. This literature highlights the importance of disentangling competitive pressure effects from input-supply effects, as well as the need to account for firm-level heterogeneity. A related strand of the literature emphasizes the role of trade policy *uncertainty* (Handley and Limão, 2022). In the context of the reduction in U.S.–China tariffs, Coelli (2025) show that the resolution of policy uncertainty fosters innovation, as measured by patenting.

From a theoretical standpoint, the effect of input-supply shocks on innovation is inherently ambiguous. On the one hand, lower input costs, higher input quality, and improved production efficiency can increase profits and relax financial constraints, thereby stimulating innovation (Bøler et al., 2015). Positive knowledge spillovers from imported intermediates may further enhance innovative capacity (Rivera-Batiz and Romer, 1991, Coe and Helpman, 1995). On the other hand, cheaper imported inputs may reduce incentives for process innovation by lowering the marginal return to efficiency-improving technologies, or induce cannibalization effects whereby firms reinforce existing production lines instead of exploring new technological trajectories (Kim, 2024). In a related framework, Atkeson and Burstein (2010) show that trade liberalization can simultaneously encourage process innovation while discouraging product innovation, generating ambiguous aggregate effects.

A central dimension of heterogeneity in this literature concerns firms' position relative to the technological frontier. In developing economies, trade liberalization may facilitate technology adoption and convergence, but can also discourage innovation in the absence of complementary institutions and policies (Baldwin and Venables, 2015). In contrast, firms closer to the frontier may experience stronger incentives to innovate when globalization lowers input costs, potentially reinforcing their competitive advantage. However, Autor et al. (2020b) highlight a further mechanism: firms with dominant market positions may use efficiency gains from global sourcing to strengthen market power and raise barriers to entry, thereby weakening their incentives to innovate. This perspective motivates empirical attention to heterogeneity across firm size, productivity, industry structure, and proximity to the frontier.

Recently, a growing literature has turned to study adverse input-supply shocks, including trade fragmentation, geopolitical risk, and supply-chain disruptions. Theoretical predictions remain ambiguous. A simple reversal of the trade liberalization mechanism suggests that higher input costs should reduce innovation by compressing margins. However, recent work emphasizes the possibility of defensive or induced innovation, whereby firms respond to input scarcity by developing substitutes or reducing dependence on vulnerable inputs. In this vein, Alfaro et al. (2025) develop a quantitative framework showing that restrictions on critical inputs (e.g., rare earth elements) can trigger directed technological change toward input-saving innovation and expand downstream sectors intensive in constrained inputs. Similarly, Flynn et al. (2025) show that exposure to geopolitical risk induces innovation aimed at reducing dependence on politically risky suppliers. Atalar (2025) further demonstrate that rising trade costs reshape buyer–supplier relationships and generate heterogeneous innovation responses among domestic suppliers: firms closer to the frontier may reduce innovation, while less advanced firms increase it in response to competitive repositioning.

Empirical evidence on trade fragmentation remains limited and is primarily conducted at the sector or industry level. Studies such as Alfaro et al. (2025) document increased innovation in downstream industries following rare earth export restrictions, while Flynn et al. (2025) show that sectors more exposed to geopolitical risk exhibit higher innovative activity and reduced reliance on vulnerable suppliers. At the firm level, Clayton et al. (2025) provide evidence that firms respond differently depending on the nature of the shock: input tariff increases mainly affect pricing behavior, while export controls are associated with greater R&D investment. Although informative, much of this evidence remains indirect, as it does not observe how firms reallocate innovation across technologies or input categories.

This emerging literature connects closely to the long-standing theory of induced innovation and directed technical change formalized in modern growth theory (e.g., Acemoglu, 2002). The central idea is that changes in relative factor prices systematically redirect innovative effort toward economizing on scarce inputs. While most empirical work has focused on labor- or energy-saving innovation, recent contributions extend this logic to trade and global value chains, emphasizing imported intermediates as a key margin of directed technological change. Related work in production networks shows that innovation and productivity spill over through input-output linkages (Acemoglu et al., 2016, Barrot and Sauvagnat, 2016). This suggests that trade shocks propagate not only within industries but across supply-chain networks, reshaping innovation incentives throughout the economy.

Despite a growing interest to study how innovation spills over to product-specific economic shocks, the only attempt is the recent study by Alfaro et al. (2025) which examines how Chinese export restrictions on rare earth elements (REE) affected innovation in downstream sectors in the rest of the world. In this attempt, they constructed an input-output table that explicitly incorporates disaggregated REE inputs, thereby allowing the authors to identify industries exposed to disruptions in the supply of critical minerals. The study then tracks innovation activity in these industries. Our approach extends this insight in several important respects. Whereas Alfaro et al. (2025) focus on a specific set of critical inputs and their downstream users, we develop a general framework that can be applied to the entire economy. By combining a patent-product concordance with a product-level production network, we are able to map patents to both directly affected products and technologically related products connected through upstream and downstream relationships. This generalization allows us to study innovation responses to a broad range of trade shocks rather than to a single strategic commodity. More broadly, our framework connects recent advances in the mapping of technological space using large-scale patent data and network methods (e.g., Bloom et al., 2013) with the literature on production networks and shock propagation (Acemoglu et al., 2016, Barrot and Sauvagnat, 2016). It is particularly suited to the analysis of imported-input price shocks, as it explicitly captures how disruptions to specific inputs propagate through supply chains and reshape firms' innovation choices.

3 Data & Methodology

Our empirical methodology consists of the following steps. First, subsection 3.1 describes the construction of the sample by combining French firm-level data with patent data. Second, subsection 3.2 identifies negative input trade shocks from structural breaks in imported input prices. Third, subsection 3.3 constructs a firm-level measure of exposure to these shocks. Fourth, subsection 3.4 links firms' patent portfolios to the products affected by the shocks to characterize the direction of innovation. Finally, subsection 3.5 presents the empirical specification used to estimate the effects of input trade shocks.

3.1 Firm-level sample construction

We build our firm-level database by merging information from four different sources. First, we rely on the *Liaisons Financières* (LIFI) database compiled by the French National Institute of Statistics and Economic Studies (INSEE) from administrative data (tax records, legal registries, etc.) and private databases (e.g., commercial ownership databases), that provides yearly detailed information on financial linkages between firms operating in France, with a particular focus on ownership structures and group affiliations. This information allows us to identify and characterize groups of firms operating in France and to determine their boundaries. Second, we rely on the *Fichier Approché des Résultats d'ESANE* (FARE) database also collected by INSEE, that combines administrative and survey data to construct annual firm-level accounts consistent with national accounting standards. The FARE database provides extensive production and financial information for the universe of individual firms operating in France from 2008. Third, we use the French customs database (DGDDI) which provides us with firm-level information on exports and imports at a very disaggregated product level (Harmonized System, 8-digit) by destination from 1993. Fourth, we rely on PATSTAT from the European Patent Office (EPO) which contains detailed information on all patent applications from different patent offices in the world.

We restrict the PATSTAT database to all priority patent applications. While the LIFI, FARE and customs databases can be matched together using the unique identifying number (siren) that is assigned to each individual firm operating in France, patent offices do not identify firms applying for patents using this number but instead use the firm's name. We therefore identify firm's siren number by exact matching of firm's name for the subset of companies located in France in the PATSTAT database. Once the four above mentioned databases have been merged, we consolidate affiliated firms by aggregating accounting, customs transactions, and patent variables at the level of the business group. Although the business group will be our unit of analysis throughout the paper, we will refer to "firms" for ease of understanding.

Because of some methodological breaks in the LIFI data between 2012 and 2014[1], our analysis focuses on the period 2014–2023. More specifically, we will use information over 2014–2015 to construct firms' exposure measures (the "share" part of our shift-share instrument) as well as predetermined firm-level controls; and information over the 2016–2023 period to construct our shocks (the "shift" part of our shift-share instrument) and analyze their impacts on firm-level innovation outcomes. As for the firm coverage, we restrict our sample in the following way. First, we focus our attention on private business groups; thus, we drop both groups consisting of a single legal entity and public entities such as administrations. Second, we drop from the sample the smallest firms with less than 10 employees in 2015, which are less likely to appear both in customs and patent data. Third, we further restrict our sample to the manufacturing sector, since our detailed customs trade data only covers trade in goods (and not in services). Lastly, we drop firms with discontinuous observation over time or with missing data in our main variables of interest. Table 1 summarizes these successive sample restrictions leading to $12,363$ firms observed in 2015,[2] $8,865$ of which are registered in customs data and 740 for which patents have been matched.

Table 2 reports the average value of various variables related to firm size, performance, trade and innovation according to their trade and patenting activity. These statistics confirm established findings: internationalized firms (either importing or exporting or both) systematically exhibit larger size (whether in terms of workforce or sales) compared to the whole sample. Similarly, these firms show superior economic performance, as evidenced by higher value added and value added per worker. Furthermore, the table reveals distinct patterns among innovators. First, innovating firms engaged in international trade are larger and more productive. Second, they display greater integration in the global economy, characterized by a broader range of imported products and trade relationships with a larger number of countries. These descriptive statistics

[1]The LIFI database underwent a major methodological redesign starting in 2012, when a survey-based system was replaced by a new framework relying on administrative and private data sources. This transition involved a complete overhaul of the identification of corporate groups and ownership links, leading to significant changes in coverage and measurement. As a result, the year 2012 and 2013 are generally considered a transition phase, and the data are only fully stabilized from 2014 onward.

[2]The sample is defined based on the final year of the pre-exposure period (2015). As some firms may subsequently exit the sample, the figures reported in Table 1 represent upper bounds.

Table 1: Number of observations by sample restriction for a reference year

	All	Customs	Patenting
Complete sample	316,916	42,569	1,427
Private groups	123,289	32,478	1,249
Workforce (> 10)	62,043	24,301	1,178
Manufacturing	13,329	9,521	772
No missing value	12,363	8,865	740

Note: The reference year is 2015. Going from left to right we restrict step by step the set of observations. The first column covers all firms observed in 2015. The second column further restricts the sample to firms for which we have recorded imports or exports in custom data in 2015. The third column further restricts the sample to firms with at least one patent identified in 2015.

underscore the close relationship between innovation and trade activities.

Table 2: Firm-level descriptive statistics for a reference year

	All	Customs	Patenting
Workforce	179.7	238.5	1,377.0
Sales	48,779.1	66,163.4	40,4354.5
Value added	14,895.0	20,096.5	12,6571.2
Value added per worker	66.6	70.4	83.1
Imported products	10.3	14.4	54.3
Importing countries	2.8	4.0	11.2
Import intensity	0.04	0.06	0.07
Patent applications	0.61	0.84	10.03
Observations	12,363	8,865	740

Note: Unweighted average of variables by firm for the reference year 2015. We step by step restrict the set of firms. The first column covers privately owned firms (excluding independent firms) for which the main activity is performed in the manufacturing sector, with at least 10 workers, observed continuously over time with no missing values. The second column further restricts the sample to firms for which we have recorded imports or exports in customs data in 2015. The third column further restricts the sample to firms with at least one patent identified in 2015. Workforce is the number full-time equivalent workers, sales and value added are expressed in thousands euros, imported products is the number of imported products, importing countries is the number of countries from which products are imported, import intensity is the value of imports divided by intermediate consumption, patent applications is the number of priority patent applications.

3.2 Estimating structural breaks in input prices

In order to measure input supply trade shocks, we rely on the BACI database from the Centre for Prospective Studies and International Information (CEPII), that provides both volumes and values of bilateral trade flows at the HS6 product level (covering more than $5,000$ manufacturing products) over the period 2007–2022. This database allows to compute yearly unit values of imports for each product-provenance pair. We use unit value fluctuations as proxy for price changes and identify structural breaks in these price changes with the following methodology. We adopt a generalized fluctuation test framework (Kuan and Hornik, 1995). While approaches based on F-statistics (e.g., Chow and supF tests) require to specify distributional assumptions on the potential underlying data generating processes with a priori candidate break points, the generalized fluctuation approach is based on parameter instability, which has particular advantages when the form of instability is unknown.[3] More specifically, we use the recursive MOSUM method (Chu et al., 1995) to detect structural breaks in prices. The methodology is articulated in three steps: we first compute the recursive residuals; then, we compute the MOSUM statistics, which consists of a moving sum of these standardized residuals; finally, we compare the statistics to critical values to identify structural breaks.

Consider the following model for a given country-product price:

$$\rho_t = \mu + u_t \tag{1}$$

where price at time $t = (1, ..., T)$ is expressed in logarithm and is denoted ρ_t, μ is a constant, and u_t are iid$(0, \sigma^2)$. Then, the recursive residuals can be expressed as:

$$\tilde{u}_t = \rho_t - \hat{\mu}_{(t-1)} \quad (t = 2, ..., T) \tag{2}$$

where $\hat{\mu}_{(t-1)}$ is the average price estimated on observations $(1, ..., t-1)$. In the absence of structural change $\forall t$, $\mu_t = \mu$ and $\tilde{u} \sim (0, \tilde{\sigma}^2)$ with $\tilde{\sigma}^2 = \frac{1}{T-1}\sum_{i=2}^{T} \tilde{u}_t^2$. Intuitively, one would expect $\tilde{u}$ to depart from zero in the case of a persistent shift of μ. Specifically, a structural price increase (decrease) will lead to a positive (negative) shift in the path of $\tilde{u}$.

The MOSUM statistics consists in the sum of a fixed number of standardized residuals in a data window whose size is determined by the bandwidth parameter $h \in (0, 1)$ and which is moved throughout the sample period. Hence, the recursive MOSUM process is defined by:

$$M(s|h) = \frac{1}{\tilde{\sigma}\sqrt{T-1}} \sum_{t=2+\lfloor Ns \rfloor}^{1+\lfloor Ns \rfloor + \lfloor Th \rfloor} \tilde{u}_t \quad (0 \leq s \leq 1-h) \tag{3}$$

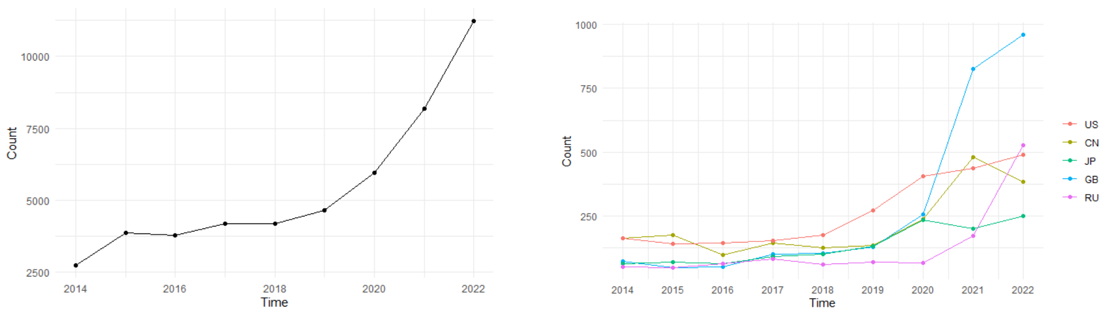
where $N = (T - \lfloor Th \rfloor)/(1-h)$ and $\lfloor Th \rfloor$ is the integer part of $T \cdot h$. Intuitively, the choice of the bandwidth parameter h introduces a tradeoff. If h is large, each moving sum includes "too many" residuals that lower the sensitivity to parameter variation. If h is small, the limiting process is not a good approximation of moving sums in finite samples, and sample variation of each moving sum is likely to be large.

The null hypothesis of "no structural change" ($\forall t$, $\mu_t = \mu$) should be rejected when the fluctuation of the MOSUM process becomes improbably large compared to the fluctuation of the limiting process. Chu et al. (1995) have demonstrated that the limiting

[3] A simpler but similar approach, based on the analysis of residuals from a product-country dummy regression, has also been recently applied by Fetzer et al. (2024).

process of moving sums of recursive residuals is the increments of a standard Brownian motion. We can reject the null hypothesis if the value of the MOSUM statistics crosses the critical values $h_\alpha(s)$ from the increments of a standard Brownian motion at the significance level α. Specifically, we classify as a price-increase structural shift if $M(s|h) > h_\alpha(s)$ at some s_0.

In order to estimate price-increase structural shifts, we aggregate all import data at the EU level and we only keep the product-provenance pairs present during the pre-period (2014–2015) in order to form a balanced panel representing $180,222$ distinct product-provenance pairs for every year. We deflate values to make unit prices comparable over time. Because the Brexit occurred during our period of analysis (in 2020), we consider the UK as a non-EU member throughout the period. A substantial quantity of product-provenance flows are null. Although the BACI methodology minimizes the likelihood of observing false zero flows for some product-provenance pairs by reconciling bilateral trade flows of export and import data, null values can occur for several reasons. These are mainly related to true zero values, prohibitive transport costs for low-value flows, or confidentiality constraints. To address this, we exclude product-provenance pairs with too low average-traded values (i.e., lower than $10,000\$$) and impute missing unit prices for single-year gaps using the average of adjacent values. Then, we apply our algorithm to identify structural breaks in unit prices on these completed series. Knowing the limited number of time periods we have, we selected a value of $h = 0.2$. For α, we selected a value of 0.32 which corresponds to classifying fluctuations of one standard deviation as structural changes based on the standard Normal distribution. For gaps exceeding one year, we interpret these as true zeros, implying infinite prices; thus, these are classified as price-increase shocks. This scenario arises, for example, in cases of economic sanctions, such as those imposed on Russia following its 2022 invasion of Ukraine.



Note: The left panel represents the number of distinct country-product pairs for which price-increase structural breaks have been estimated for each year. There are 180,222 distinct country-product pairs for every year. The right panel represents the number of distinct products for which price-increase structural breaks have been estimated for each year and for a set of specific countries. Countries include: the United States (US), China (CN), Japan (JP), Great Britain (GB) and Russia (RU).

Figure 1: Estimated price-increase structural breaks

Figure 1 represents estimated price-increase structural breaks. Specifically, the left panel reports the annual number of distinct product-provenance pairs for which a structural increase in import prices is detected. The figure shows a modest rise in 2015, followed by a relatively stable period until 2019. Beginning in 2019, the number of product-provenance pairs exhibiting structural price increases rises sharply, accelerating further after 2020. This pattern is consistent with the emergence of large global supply-side shocks that affected international trade during the subsequent years. Although the timing suggests a connection with the COVID-19 pandemic and the associated disruptions to global value chains, the upward trend appears to have started slightly before the onset of the pandemic, indicating that additional factors may also have contributed to the increase in import-price pressures.

A limitation of this Figure is that each product-provenance pair receives equal weight regardless of its economic importance. To better characterize the underlying dynamics, the right panel reports the number of products experiencing structural price increases for a selection of major trading partners of the European Union: the United States, China, Japan, Great Britain, and Russia. Several common patterns emerge. For all countries considered, the number of detected price increases remains relatively stable until 2019 where a first increase is observed for the United States. One possible explanation is the disruption of global production networks and trade flows associated with the escalation of trade tensions during the first Trump administration. For China, Japan, and Great Britain, the number of products affected by structural price increases rises markedly in 2020, coinciding with the outbreak of the COVID-19 pandemic. This finding is consistent with evidence that pandemic-related lock-downs, transport bottlenecks, port congestion, and shortages of intermediate inputs generated substantial increases in international trade costs and import prices (e.g., Bai et al., 2024). The Chinese case is particularly noteworthy, as the increase amplifies through 2021. This persistence is consistent with China's zero-COVID strategy, which generated repeated production interruptions and logistics disruptions in several major manufacturing and export hubs. Given China's central position in global value chains, such disruptions are likely to have propagated internationally, contributing to sustained import-price pressures for a wide range of products. Great Britain exhibits a pronounced spike in 2021, which likely reflects the implementation of Brexit. The introduction of customs procedures, rules-of-origin requirements, and additional administrative barriers increased trade frictions between Great Britain and the European Union, particularly for highly integrated cross-border supply chains. Finally, imports from Russia display a sharp increase in 2022, coinciding with Russia's invasion of Ukraine and the subsequent economic sanctions imposed by the European Union. In terms of data, this specific case translates into the appearance of many zero flows which are classified as price-increase shocks by our algorithm.

Taken together, these results suggest that the estimated structural price increases capture economically meaningful shocks affecting international trade. The timing of the detected breaks aligns closely with major disruptions to global supply chains, geopolitical tensions, and changes in trade policy. This correspondence provides indirect validation of the empirical approach and supports the interpretation that structural breaks in import prices reflect persistent increases in trade costs and supply-chain frictions rather than transitory price fluctuations.

3.3 Measuring firm exposure to trade shocks

To measure the exposure of firms to trade shocks, we adopt a shift-share design approach. Consider a French firm i importing a product p from provenance c at an initial date t_0. Let $I_{p,c,t}$ denotes a dichotomous variable indicating whether there is a price-increase shock for imported products p from provenance c at time t. The exposure of firm i to input supply trade shocks at time t is measured as:

$$Z_{i,t} = \sum_{p,c} \omega_{i,p,c,t_0} \times I_{p,c,t} \tag{4}$$

where ω_{i,p,c,t_0} is the relative importance of product p from provenance c for firm i at t_0, defined as firm i's import of product p from provenance c divided by total intermediate input consumption of firm i at t_0. Therefore, the firm exposure to input supply trade shocks is the cumulative (predetermined) relative importance of each import flow in the production process of the firm which has been impacted at a given time. A key advantage of this approach is its flexibility, which allows us to restrict the set of products to specific subsets in order to measure exposure to particular categories of imported inputs, such as critical or strategic products.

It is important to stress that the time variation in our measure of exposure $Z_{i,t}$ only stems from EU import prices and not from the firm-level weights, which are fixed at their value in the initial period t_0. One could expect that a firm's innovation response at time $t > t_0$ will induce changes to its pattern of imports, including both intensive margin responses (changes in imported value for a previously imported product p from a provenance c) and extensive margin responses (changes in the set of products p sourced across provenances c). By fixing the firm-level weights in the initial period t_0, we exclude this subsequent endogenous variation in imports from our measure of exposure. This is a Bartik-type shift-share instrument — similar to that used in Aghion et al. (2024) — except for the fact that the shift component is dichotomous rather than continuous. In our case, the sum of exposure weights ω_{i,p,c,t_0} across (p, c) might be different from 1 and varies across firm. Then, we follow Borusyak et al. (2018) who argue that in such "incomplete shift-share" case with panel data, one needs to control for this sum interacted with a time dummy in the regressions.

As already mentioned, we consider the period 2014–2015 as our predetermined period t_0. Weights ω_{i,p,c,t_0} are computed by dividing the sum of import flows by the sum of total intermediate input consumption over this period. In order to deal with potential outliers, we trim our measure of exposure by eliminating weights lower than 0.01 and exposure scores above the $99th$ percentile. Then, we consider a firm as impacted by any shock, if its exposure score $Z_{i,t}$ is strictly positive.

Figure 2 reports the evolution of the share of firms affected by imported-input price-increase shocks in France for both the sample of manufacturing firms and the subset of innovating firms (i.e., firms which patented at least once during the whole period). The figure displays the proportion of firms whose imported intermediate inputs experienced

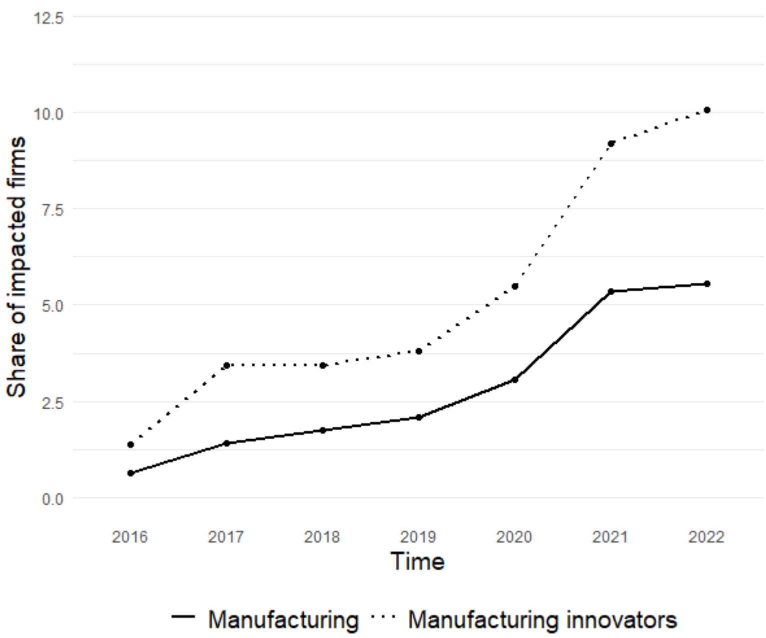


Figure 2: Impacted firms

Note: The ratio of firms impacted by price-increase structural breaks is reported over time. A firm is considered as impacted if its exposure is strictly positive. The solid line represents the sample of privately owned firms (excluding independent firms) for which the main activity is performed in the manufacturing sector, with at least 10 workers, observed continuously over time with no missing values (9,910 observations per year in average). The dashed line further restricts the sample to firms with at least one patent identified in 2014–2023 (1,647 observations per year in average).

a structural price-increase in a given year for each sample. The sharp rise in imported-input price shocks documented in Figure 1 is clearly reflected at the firm level. Among manufacturing firms, the share of impacted firms increased from approximately 1% in 2016 to 5.5% in 2022. The increase is even more pronounced among manufacturing innovators, for which the corresponding share rose from 1.5% to 10.5% over the same period. These results suggest that the widespread disruptions affecting international trade penetrated deeply into the French economy. Importantly, Figure 2 is likely to understate the overall economic significance of these shocks. By construction, the figure only captures the incidence of newly detected structural price increases in each year. However, structural breaks represent persistent changes in input prices rather than temporary fluctuations. Consequently, firms affected in a given year continue to face higher input costs in subsequent periods, implying that the cumulative exposure of the economy to imported-input shocks is substantially larger than suggested by the annual incidence rates alone. This distinction is particularly relevant in the context of international sourcing, where firms often face adjustment costs and long-term supplier relationships that limit their ability to rapidly substitute away from more expensive foreign inputs. Persistent increases in imported-input costs may therefore generate long-lasting effects on firms' production decisions, profitability, and competitiveness.

A second notable finding is the substantially greater exposure of innovative firms. Throughout the period, manufacturing innovators are almost twice as likely as the average manufacturing firm to experience imported-input price shocks. Several mechanisms may explain this pattern. First, innovative firms are generally more integrated into international markets and global value chains as shown in Table 2. Specifically, innovative firms tend to rely more heavily on imported intermediate goods, particularly technologically sophisticated or specialized inputs that may be unavailable domestically. Access to such inputs is often an important determinant of productivity growth, product quality upgrading, and innovation performance (Halpern et al., 2015). As a result, firms operating closer to the technological frontier may be disproportionately exposed to disruptions affecting international sourcing. Second, the relationship may also reflect a causal effect running in the opposite direction. Economic theory suggests that increases in input costs can induce firms to reorganize production, adopt new technologies, or develop new products in order to preserve profitability. In this perspective, trade shocks may stimulate innovation as an adaptation strategy. By exploiting the timing and variation of firm's exposure to trade shocks, our identification strategy allows us to distinguish whether innovative firms are more exposed because they are intrinsically more dependent on foreign inputs, or whether exposure to trade shocks itself influences firms' innovative behavior and economic performance.

3.4 Measuring firms' direction of innovation

To identify the technological direction of firms' innovative activities, we develop a novel methodology that links firms' patent portfolios to the imported products affected by structural price shocks. Our approach combines two complementary sources of information. First, we rely on a patent-product concordance developed by Lybbert and Zolas

(2014), which provides probabilistic links between patent classifications and product classifications. Second, we exploit a product-level input-output network developed by Fetzer et al. (2024), which captures upstream and downstream production linkages between products. Together, these two building blocks allow us to trace the relationship between firms' patented technologies and the products exposed to import-price shocks, both directly and indirectly through production-network connections.

Let us define the subset of impacted products at any t and from any country c for firm i, $P_i = \{p \in P \,|\, \forall c, \forall t, \, I_{p,c,t} = 1, \, \omega_{i,p,c,t_0} > 0\}$. Let $j \in J_i$ indexes patents owned by firm i where each patent is associated to potentially many technologies $s(j) \in S$. Using an algorithmic links with probabilities methodology, Lybbert and Zolas (2014) have constructed a concordance between technology and product spaces represented by probabilities w_{sp} linking each technological field $s \in S$ to product $p \in P$. Then, the firm's i patent portfolio can be represented in the product space and one can measure the weight of patents related to the subset of impacted products P_i by summing the weights for this specific subset of product:

$$W_i^P = \sum_{j \in J_i} \sum_{p \in P_i} w_{sp}(j). \tag{5}$$

Therefore, W_i^P represents the cumulated patent weights which are associated to firm's i impacted products. Note that W_i^P can sum up to the total number of patents and it measures the subset of the firm portfolio which is directly related to impacted products, in the sense that they belong to the same product category p.

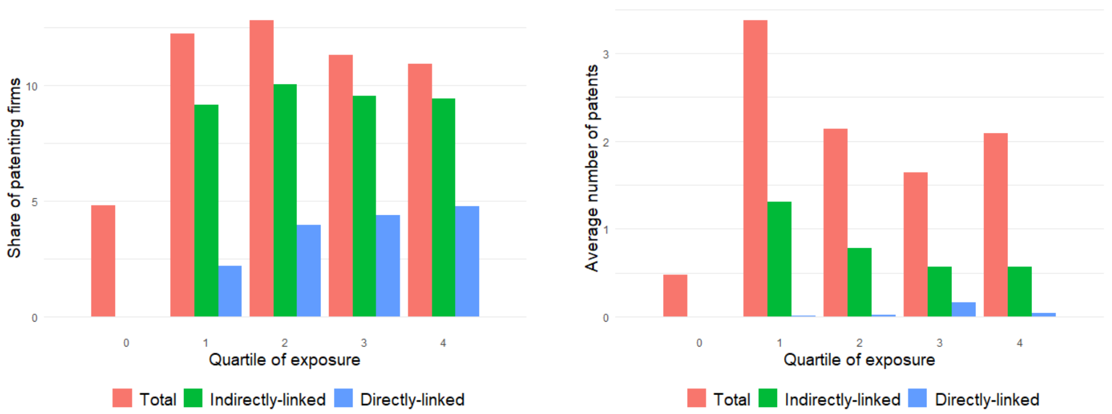
Furthermore, one might be interested in identifying patents which are indirectly related to impacted products through production-network connections via upstream or downstream linkages. Using a Large Language Model (LLM) with prompt engineering, Fetzer et al. (2024) have constructed the production network represented by input-output relationships linking each input product to output product. Then, the set of products P represents the set of nodes of the network and $A = (a_{pq})_{p,q \in P}$ is the adjacency matrix of an undirected network, where $a_{pq} = 1$ represents a connection between product p and product q and $a_{pq} = a_{qp}$. This reflects the fact that one product is an input of another product or vice versa. Then, one can define the subset of products P_i' which are connected to firm's i impacted products:

$$P_i' = \{p \in P \,|\, \exists q \in P_i \text{ s.t. } a_{pq} = 1\}. \tag{6}$$

Intuitively, P_i' represents all products which are required to produce impacted imported input goods by firm i or which are produced from impacted imported input goods by firm i. Then, it is possible to measure the weight of patents related to those products for firm's i by replacing P_i by P_i' in Equation (5):

$$W_i^{P'} = \sum_{j \in J_i} \sum_{p \in P_i'} w_{sp}(j). \tag{7}$$

Figure 3 reports the share of patenting firms across different levels of firms' exposure to trade shocks (left panel) and the corresponding average number of patents (right



Note: The left panel reports the share of patenting firms by level of exposure to trade shocks. The right panel reports the average number of patents by exposure level. Three patent variables are considered: total patents (red), directly linked patents (blue), and indirectly linked patents (green). Exposure is measured on a five-level scale, where 0 denotes no exposure and 1–4 correspond to the respective quartiles of the exposure distribution. Exposure scores are cumulated over the 2016—2023 period. The sample consists of privately owned manufacturing firms (excluding independent firms) with at least 10 employees that are observed continuously over the 2016-–2023 period without missing values.

Figure 3: Innovation activity by level of exposure to trade shocks

panel). Following the methodology described above, patenting activity is measured using three variables: total patents, patents directly related to impacted products, and patents indirectly related to impacted products. Exposure is measured on a five-level scale, where 0 denotes no exposure and levels 1-–4 correspond to the quartiles of the exposure distribution. Exposure scores are accumulated over the 2016—2023 period. The sample includes privately owned manufacturing firms (excluding independent firms) with at least 10 employees that are continuously observed between 2016 and 2023 without missing values. The results show that both the share of patenting firms and the average number of patents are substantially higher among firms exposed to trade shocks than among unexposed firms. This pattern is consistent with Figure 2, which shows that innovative firms are more likely to be exposed to trade shocks. More interestingly, total patenting activity exhibits a non-monotonic relationship with exposure. Although patenting remains higher among exposed firms than among unexposed firms, firms in the highest exposure quartile display lower patenting activity than those in the intermediate exposure groups, both at the extensive and intensive margins. A different pattern emerges for patents directly related to impacted products. Here, greater exposure is generally associated with more innovation in directly affected technological domains, both in terms of the likelihood of patenting and the average number of patents. However, the difference between the third and fourth exposure quartiles appears relatively small and may not be statistically significant. By contrast, patents indirectly related to impacted products display no evidence of a positive relationship with exposure. While the propensity to patent in indirectly related domains remains broadly stable across exposure levels, the average number of such patents declines as exposure increases.

Taken together, these correlations suggest that adverse imported input shocks is positively correlated with overall innovation, although the relationship is non-linear. The lower innovation observed among the most exposed firms may reflect countervailing mechanisms, such as reduced profitability or tighter financial constraints, which limit firms' ability to sustain innovation efforts. Beyond the intensity of innovation, these results suggest a reallocation of innovation associated with trade shocks. Specifically, innovation becomes increasingly concentrated in technological domains directly related to impacted products, whereas innovation in indirectly related domains declines with exposure. This pattern is consistent with a reallocation of innovative effort across technological domains, although multiple offsetting mechanisms may contribute to the observed relationships. Since the evidence presented here is purely descriptive, the causal analysis in the following sections aims to disentangle these competing effects.

3.5 Estimation strategy

This section presents our baseline empirical specification for estimating the effect of exposure to input trade shocks on firm innovation. Our identification strategy combines a shift-share measure of firm-level exposure with a specification in difference including fixed effects and a set of predetermined controls. Intuitively, identification comes from comparing firms that differ in their exposure to product-level trade shocks, while controlling for time-invariant firm characteristics, industry-specific trends, and predetermined differences in firm characteristics. Our identifying assumption is that, conditional on these controls, changes in firms' exposure to input trade shocks are orthogonal to unobserved firm-specific determinants of future innovation. Formally, after accounting for common time effects, sectoral unobservables, and predetermined firm characteristics, firms experiencing larger increases in exposure should not systematically differ from less exposed firms in terms of their underlying innovation trajectories. A key implication of this assumption is the absence of differential pre-trends in innovation prior to the realization of trade shocks. We will assess the plausibility of this assumption through a series of placebo. We restrict our analysis to the subset of innovating firms (i.e., firms with at least one patent application between 2014 and 2023). Out of our sample of 12,363 firms (see Table 1), there are 1,744 such innovators. Not all of them are active throughout our sample period. On average across those years there are 586 innovators in our sample (5.9% of 9,910 firms operating in a given year).

We estimate the effect of exposure to input trade shocks on innovation using the following equation:

$$\Delta_3 \tilde{Y}_{i,t+3} = \beta\, \Delta_1 \tilde{Z}_{i,t} + \delta\, X_{i,t_0} + \tilde{\delta} \left(\tilde{X}_{i,t_0} \times \gamma_t \right) + \gamma_t + \epsilon_{i,t}. \tag{8}$$

The dependent variable, $\Delta_3 \tilde{Y}_{i,t+3}$, measures the evolution of innovation outcomes over a three-year horizon. We consider two complementary measures of innovation. The first captures the extensive margin and is equal to one if the firm files at least one patent application between t and $t+3$. The second captures the intensive margin and is defined as the change in the logarithm of one plus the number of patents over the same period. For each of these measures, we will consider three patent metrics: the *total number of patents*, the *number of patents directly related to the shocks* derived from Equation (5), and the *number of patents indirectly related to the shocks* derived from Equation (7). The use of a multi-year horizon is motivated by the fact that innovative activities are inherently dynamic and that firms may require time to adjust their research strategies and generate patentable inventions following a trade shock. Our main explanatory variable, $\Delta_1 \tilde{Z}_{i,t}$, corresponds to the annual change in the logarithm of one plus firm-level exposure to input trade shocks between years $t-1$ and t. Therefore, the coefficient β measures whether firms experiencing a larger increase in exposure subsequently exhibit stronger or weaker innovative performance over the following three years.

Because the specification is estimated in differences, it removes all time-invariant firm characteristics that could jointly influence innovation outcomes and firms' exposure to imported-input shocks (e.g., technological capabilities, long-run sourcing strategies). Consequently, identification relies exclusively on within-firm variation in exposure over time. The model additionally includes year fixed effects γ_t which absorb aggregate shocks affecting all firms simultaneously, such as macroeconomic fluctuations, changes in patenting incentives, or economy-wide disruptions to international trade. Following Blundell and Robin (1999) and Blundell and Dias (2002), we use a control-function approach based on predetermined firm characteristics X_{i,t_0} measured at t_0 which includes: average sales, average employment, average value added per worker, number of patent applications. This allows us to account for potential correlations between changes in exposure, firms' innovation potential and observable firm characteristics. We also include sector fixed effects (NACE, 2-digit) in X_{i,t_0} in order to account for industry-specific trends. These controls will be used in all the specifications we test in Section 4. Our specification also follows recent advances in the shift-share literature. Firm-level exposure is constructed by combining predetermined import structures with time-varying product-level shocks. As emphasized by Borusyak et al. (2018), identification in panel shift-share settings may be threatened when units with different initial exposure shares follow distinct underlying trends. To address this concern, we include interactions between year fixed effects and two predetermined measures of firms' import structures included in $\tilde{X}_{i,t_0}$: overall import intensity and the import intensity of products eventually exposed to shocks. These interactions allow firms with different initial sourcing patterns to follow flexible time paths and therefore absorb differential trends associated with pre-existing import dependence.

The empirical specification can thus be interpreted as a conditional difference-in-differences design, in which firms are continuously treated according to their exposure to product-level trade shocks. The identifying variation arises from differences in the timing and intensity of exposure across firms that originate from predetermined import baskets rather than from contemporaneous innovation decisions. Finally, standard errors are clustered at the firm level to account for serial correlation in innovation outcomes and exposure measures within firms over time. In addition, we conduct placebo exercises that regress past innovation outcomes on contemporaneous exposure shocks. Under the identifying assumption, future trade shocks should not predict past innovation outcomes. Failure to reject this null hypothesis would provide support for the absence of pre-existing differential innovation trends.

4 Empirical Analysis

The empirical analysis is organized into three parts. First, subsection 4.1 presents the baseline results and evaluates the validity of the empirical strategy through a placebo test. Subsection 4.2 then explores heterogeneity in the estimated effects according to firm characteristics. Finally, subsection 4.3 examines how the estimated effects vary across industries.

4.1 Estimated effects of firm exposure on innovation

This section examines how firms' exposure to input trade shocks affects innovation activities and, more specifically, the direction of innovative efforts. Table 3 reports estimates of Equation (8) using alternative measures of firms' patenting activity as dependent variables. The column labeled "Total" considers all patent applications filed by the firm, while the columns "Directly-linked" and "Indirectly-linked" focus on patent applications related, respectively, to products directly affected by the input trade shocks and to products indirectly connected to the affected products, such as upstream inputs or downstream outputs. For each measure, we consider two outcomes. The "patenting" column captures the *extensive margin* of innovation and is defined as an indicator equal to one if the firm filed at least one patent application between t and $t+3$. The "number of patents" column captures the *intensive margin* and is measured as the logarithm of one plus the number of patent applications filed over the same period.

The results reveal that exposure to input trade shocks affects overall innovation activity positively. Firms facing stronger shocks exhibit a higher propensity to patent and a greater number of patent applications. Although the estimated coefficients consistently point toward a positive relationship between exposure to input trade shocks and innovative activity, the estimated effect on the extensive margin is not statistically significant and the effect on the intensive margin is significant only at the 10% level. More importantly, the results suggest that the effect of input trade shocks is highly heterogeneous across technological domains, suggesting a change of innovation direction. We find no evidence that firms increase innovation in domains directly related to the products affected by the shocks. Neither the probability of patenting nor the number of patent applications in directly affected technological classes responds significantly to increased exposure. This absence of a direct response suggests that firms may face substantial technological, organizational, or regulatory barriers that limit their ability to innovate within the precise domains exposed to the shock. In many industries, production technologies are characterized by significant adjustment costs, path dependence, and accumulated knowledge requirements, making rapid innovation in core technologies particularly difficult. In contrast, we find strong evidence that firms increase innovation

Table 3: Estimated effects of input price increase on patenting activity

	Total		Directly-linked		Indirectly-linked	
	Patenting	Number of patents	Patenting	Number of patents	Patenting	Number of patents
$\Delta \ln Z_{i,t}$	0.458	1.531*	0.649	-0.134	1.845***	1.459**
	(0.506)	(0.851)	(0.468)	(0.156)	(0.645)	(0.596)
Controls	X	X	X	X	X	X
Year F.E.	X	X	X	X	X	X
Sector F.E.	X	X	X	X	X	X
Observations	7,911	7,911	7,911	7,911	7,911	7,911
R^2	0.03	0.04	0.17	0.20	0.18	0.11

Note: This table reports estimates of Equation (8) for alternative measures of firms' patenting activity as dependent variables: total patents, directly-linked patents, and indirectly-linked patents. For each measure, the "patenting" column uses an indicator equal to one if the firm filed at least one patent application between t and $t+3$, while the "number of patents" column uses the logarithm of one plus the number of patent applications filed in the same period. All specifications include the following predetermined (in t_0) firm-level controls: average sales, average workforce, average value added per worker, number of patent applications, sector fixed effects (NACE, 2-digit), and the import share of products with price-increase structural breaks and total import share, both interacted with year fixed effects. Estimates are obtained by OLS, with standard errors clustered at the firm level. Time period for t: 2016–2020. p-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

activities in technological domains indirectly connected to the impacted products. Exposure to input trade shocks significantly increases both the likelihood of patenting and the number of patent applications related to upstream, downstream, or technologically adjacent products. This pattern suggests that firms respond to input trade shocks not by innovating within the affected technological domain itself, but rather by redirecting innovative efforts toward adjacent products. Such a response is consistent with the literature on knowledge recombination and localized technological search, which argues that firms tend to develop innovations by exploiting capabilities that are close to their existing knowledge base. Faced with disruptions in input markets, firms may therefore seek alternative inputs, redesign production processes, improve compatibility between intermediate goods, or develop substitute products in related technological areas. Input trade shocks consequently appear to act as catalysts for technological diversification and adaptation rather than direct innovation within affected product categories.

When firms experience disruptions in the availability or cost of imported inputs, innovation may serve as a mechanism for reducing dependence on vulnerable supply chains. From this perspective, innovation can be seen as a *defensive* strategy aimed at mitigating or escaping the shock. However, rather than replacing affected inputs directly, firms appear to adjust through innovations occurring elsewhere in the value chain. The positive response observed in connected technologies is therefore consistent with a process of innovation reallocation, whereby firms modify the direction of technological efforts in order to preserve production efficiency and adapt to changing input conditions. From a broader perspective, the results suggest that input trade shocks influence not only the level of innovation but also its composition. While the effect on aggregate patenting activity is negligible, the underlying adjustment operates primarily through innovation in related technological domains. This distinction is important because it highlights a mechanism through which trade-induced shocks can reshape firms' technological trajectories and patterns of knowledge accumulation without necessarily generating innovation in the technologies directly exposed to the shock.

To address potential identification concerns, our empirical specification exploits variation in exposure growth rates, thereby eliminating the influence of time-invariant firm characteristics that may be correlated with exposure levels. We further account for potential correlations between changes in exposure and observable firm characteristics through a set of predetermined controls. Sector and year fixed effects absorb common shocks at the industry and time levels, while interactions between year fixed effects and import exposure measures account for differential trends associated with firms' import structures. In addition, we conduct placebo tests based on pre-exposure innovation outcomes. The results, reported in Table A1 in the Appendix, reveal no significant relationship between contemporaneous input trade shocks and past patenting activity, providing support for the identifying assumption that future exposure is orthogonal to pre-existing innovation trends.

4.2 Heterogeneity of the effect by firm characteristics

This section investigates whether the effect of firms' exposure to input trade shocks on innovation varies across firm characteristics. The literature in economics of innovation has long established that firms differ substantially in their ability to identify, absorb, and exploit new technological opportunities (Nelson, 1991). Consequently, the innovative response to external shocks may depend on firms' pre-existing innovation capabilities, technological position, size, and productivity. First, prior innovation experience may facilitate firms' adjustment to input trade shocks. Innovation activities are characterized by substantial fixed and sunk costs associated with establishing R&D capabilities, hiring specialized employees, accumulating technological knowledge, and developing organizational routines. Firms that have already engaged in innovative activities may therefore face lower marginal costs of undertaking additional innovation projects. This argument is consistent with the literature on cumulative innovation and absorptive capacity, which emphasizes that past innovation enhances firms' ability to recognize and exploit new opportunities (Cohen and Levinthal, 1989, Klette and Kortum, 2004). To examine this channel, we construct a binary variable, Innovator_{t_0}, equal to one if the firm had filed at least one patent application during the pre-exposure period t_0, and zero otherwise. In our sample, 44.3% of firms are classified as prior innovators.

Second, firms located closer to the technological frontier may be particularly well positioned to react to changes in input market conditions. Frontier firms typically possess larger stocks of technological knowledge, stronger research capabilities, and greater access to skilled human capital, allowing them to transform new opportunities into innovative outputs more effectively. Theoretical and empirical contributions have highlighted the role of knowledge accumulation and technological leadership in shaping firms' innovation dynamics (Aghion et al., 2005, Acemoglu et al., 2006). To capture this dimension, we construct a binary variable, $\text{Patents}^{H}_{t_0}$, equal to one if the firm's patent stock in period t_0 exceeds the median value observed within its industry (NACE, 2-digit), and zero otherwise. According to this definition, 23.2% of firms in our sample are classified as operating at the knowledge frontier.

Third, firm size may play an ambiguous moderating role. On the one hand, larger firms generally possess greater financial resources, larger pools of human capital, and easier access to external financing, which may facilitate the reallocation of resources toward innovative activities following a shock. On the other hand, organizational complexity, bureaucratic rigidities, and slower decision-making processes may limit their ability to adapt rapidly. This ambiguity has long been discussed in the literature following Schumpeter's distinction between entrepreneurial and large-corporation regimes of innovation and the debate on the "Schumpeterian hypotheses" about the relationship between firm's size, market structure, and innovation (Cohen, 2010). To investigate the role of size, we construct a binary variable, $\text{Sales}^{H}t_0$ equal to one when a firm's average sales exceeds the median value observed within its industry (NACE, 2-digit) during period t_0. Based on this definition, 78.0% of firms in our sample are classified as large.

Finally, firm productivity may influence the innovative response to input trade shocks. The trade and innovation literature has consistently documented that more productive firms are more likely to engage in international markets and to undertake innovative activities (Guerini et al., 2021). In heterogeneous-firm models, productivity enhances firms' ability to bear the fixed costs associated with innovation and technology adoption, while empirical evidence suggests that productive firms exhibit stronger innovative performance and greater responsiveness to market opportunities (Melitz, 2003, Bustos, 2011). To explore this dimension, we construct a binary variable, $\text{Productivity}^{H}_{t_0}$, equal to one if the firm's labor productivity — measured as value added per worker — exceeds the median value observed within its industry (NACE, 2-digit) in period t_0. Using this definition, 63.8% of firms in our sample are classified as belonging to the productivity frontier.

In order to test empirically for heterogeneity of the effect, we allow our main estimated effect in Equation (8) to interact with firm characteristics:

$$\Delta_3 \tilde{Y}_{i,t+3} = \beta\, \Delta_1 \tilde{Z}_{i,t} + \alpha \left(\Delta_1 \tilde{Z}_{i,t} \times W_{i,t_0}\right) + \theta\, W_{i,t_0} + \delta\, X_{i,t_0} + \tilde{\delta} \left(\tilde{X}_{i,t_0} \times \gamma_t\right) + \gamma_t + \epsilon_{i,t} \quad (9)$$

where W_{i,t_0} is a binary variable equal to one if the firm has a specific characteristic at t_0 and zero otherwise. Then, the coefficient α captures the difference in the effect of exposure to trade shocks on innovation between firms with and without this specific characteristic. Table 4 presents estimates of Equation (9) for alternative measures of firms' patenting activity as dependent variables. Column labels retain the meaning from Table 3.

We uncover substantial heterogeneity in the effect of input trade shocks on firms' innovation activities. Overall, the findings suggest that firms' pre-existing capabilities and organizational characteristics play an important role in determining their ability to transform changes in input market conditions into innovative outcomes. First, we

Table 4: Estimated effects of input price increase on patenting activity (firm-level heterogeneity)

	Total		Directly-linked		Indirectly-linked	
	Patenting	Number of patents	Patenting	Number of patents	Patenting	Number of patents
$\Delta \ln Z_{i,t}$	1.348*	1.198	0.132	0.028	2.814***	0.978*
	(0.719)	(0.834)	(0.563)	(0.180)	(0.859)	(0.524)
$\Delta \ln Z_{i,t} \times \text{Innovator}_{t_0}$	-1.673*	0.501	0.897	-0.290	-1.772	0.824
	(0.988)	(1.623)	(0.876)	(0.242)	(1.185)	(1.095)
Innovator_{t_0}	0.200***	0.198***	0.046***	0.005*	0.113***	0.067***
	(0.016)	(0.021)	(0.010)	(0.003)	(0.015)	(0.010)
$\Delta \ln Z_{i,t}$	0.389	0.586	-0.053	-0.023	1.803**	0.555
	(0.681)	(0.804)	(0.435)	(0.138)	(0.824)	(0.487)
$\Delta \ln Z_{i,t} \times \text{Patents}^H_{t_0}$	-0.364	1.895	1.778*	-0.317	-0.130	2.269*
	(0.941)	(1.872)	(0.834)	(0.294)	(1.294)	(1.307)
$\text{Patents}^H_{t_0}$	0.272***	0.324***	0.057***	0.009	0.121***	0.084***
	(0.018)	(0.028)	(0.015)	(0.006)	(0.021)	(0.016)
$\Delta \ln Z_{i,t}$	2.553***	2.835**	1.589	0.256	4.852***	2.421***
	(1.075)	(1.361)	(1.078)	(0.418)	(1.221)	(0.791)
$\Delta \ln Z_{i,t} \times \text{Sales}^H_{t_0}$	-2.441**	-1.568	-1.078	-0.439	-3.439**	-1.114
	(1.222)	(1.656)	(1.196)	(0.436)	(1.394)	(1.019)
$\text{Sales}^H_{t_0}$	0.127***	0.146***	0.032***	0.002	0.093***	0.050***
	(0.019)	(0.020)	(0.010)	(0.003)	(0.014)	(0.008)
$\Delta \ln Z_{i,t}$	1.330	3.921**	1.414**	-0.238	2.773*	3.265***
	(0.855)	(1.655)	(0.714)	(0.454)	(1.640)	(0.808)
$\Delta \ln Z_{i,t} \times \text{Productivity}^H_{t_0}$	-1.172	-3.157*	-1.013	0.133	-1.261	-2.376**
	(1.056)	(1.911)	(0.911)	(0.451)	(1.792)	(1.058)
$\text{Productivity}^H_{t_0}$	0.069***	0.084***	0.032***	0.004	0.101***	0.047***
	(0.020)	(0.024)	(0.011)	(0.004)	(0.016)	(0.010)
Controls	X	X	X	X	X	X
Year F.E.	X	X	X	X	X	X
Sector F.E.	X	X	X	X	X	X
Observations	7,911	7,911	7,911	7,911	7,911	7,911

Note: This table reports estimates of Equation (9) for alternative measures of firms' patenting activity as dependent variables: total patents, directly-linked patents, and indirectly-linked patents, and for alternative firm-level moderating variables. For each measure, the "patenting" column uses an indicator equal to one if the firm filed at least one patent application between t and $t+3$, while the "number of patents" column uses the logarithm of one plus the number of patent applications filed in the same period. Each specification is estimated separately for each moderating variable. Moderating variables are binary indicators equal to one if the corresponding firm-level characteristic is above the sectoral median (NACE, 2-digit): total number of patents, average sales, average workforce, average value added per worker. All specifications include the following predetermined (in t_0) firm-level controls: average sales, average workforce, average value added per worker, number of patent applications, sector fixed effects (NACE, 2-digit), and the import share of products with price-increase structural breaks and total import share, both interacted with year fixed effects. Estimates are obtained by OLS, with standard errors clustered at the firm level. Time period for t: 2016–2020. p-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

find positive and statistically significant effects of input trade shocks on the propensity to patent among firms that were not innovators during the pre-exposure period. This result indicates that input trade shocks can induce innovation entry by firms that had previously remained outside the innovation process. One possible explanation is that such shocks increase the returns to innovation by altering input availability, input quality, or production costs, thereby encouraging firms to undertake innovative investments despite the fixed costs associated with innovation activities. Interestingly, this effect was masked in the aggregate estimates by a composition effect: firms with a prior history of innovation are substantially more likely to patent on average, but their innovative activity is less responsive to input trade shocks. This finding is consistent with the idea that incumbent innovators may already operate close to their desired innovation intensity and therefore exhibit lower marginal responses to new opportunities. At the same time, the evidence reveals a different pattern among firms located at the knowledge frontier. Firms with above-median patent portfolios exhibit a significantly stronger innovative response to input trade shocks. In particular, they are more likely to initiate patenting activity in technological domains directly related to the impacted products, while also increasing patent production in technological fields indirectly connected to those products. Firms at the knowledge frontier may be better able to identify, evaluate, and exploit new technological opportunities generated by changes in input markets. Their existing technological capabilities allow them not only to innovate within directly affected domains but also to recombine knowledge across related technological fields, generating broader innovation spillovers. The distinction between direct and indirect patenting responses further suggests that technologically advanced firms are particularly effective at leveraging input trade shocks to expand their innovation activities beyond narrowly defined product areas.

The results also point to an important role for firm size as measured by sales. Specifically, the positive impact of input trade shocks on the propensity to patent —– both overall and in technological domains indirectly connected to the affected products —– is concentrated among smaller firms. Aggregate estimates reveal a composition effect: larger firms patent more on average but respond less strongly to input trade shocks. This pattern suggests that organizational flexibility may outweigh resource availability in shaping firms' responses. While larger firms possess greater financial and human resources, they may also face greater bureaucratic complexity, coordination costs, and organizational inertia, which can slow the reallocation of resources toward new innovative projects. Smaller firms, by contrast, may be better positioned to rapidly adjust their innovation strategies when new opportunities arise. An alternative explanation is that imported input price shocks have a weaker impact on larger firms, not because of organizational inertia, but because their greater scale and financial resources provide a buffer that reduces the marginal incentive to respond to increases in imported input prices. Finally, we find that highly productive firms exhibit weaker innovation responses to input trade shocks, particularly in terms of the number of patents produced overall and in technological domains indirectly related to the affected products. Despite being in line with the traditional view that more productive firms are generally more innovative in average, our findings nuance it by revealing that the most productive firms are less responsive to input trade shocks. This might be consistent with the idea that highly productive firms may already operate close to their technological optimum and therefore have fewer opportunities for additional innovation induced by external shocks. Alternatively, productivity leaders may rely on established production processes and innovation trajectories that are less sensitive to changes in input market conditions. In contrast, less productive firms may view such shocks as opportunities to upgrade technologies, reorganize production, or explore new innovation pathways, leading to stronger patenting responses.

In summary, these findings suggest that input trade shocks stimulate innovation primarily among firms that retain sufficient scope for technological adjustment while simultaneously possessing the organizational flexibility or knowledge assets required to exploit new opportunities.

4.3 Heterogeneity of the effect by industry type

This section investigates whether the effect of firms' exposure to input trade shocks on innovation varies across industries. While some industries may be considered as strategic in terms of economic resilience and strategic autonomy, their adjustment capacities may differ substantially due to variations in technological opportunities, production technologies and regulatory environments leading to heterogeneous innovation responses to input trade shocks.

First, we consider industries characterized by particularly stringent production constraints and safety requirements. In sectors involving hazardous production processes, firms typically operate under strict regulatory frameworks, rely on highly specialized capital equipment, and employ workers with industry-specific skills. These characteristics may limit firms' flexibility in adjusting production processes following changes in input market conditions, but they may also increase incentives to innovate when disruptions threaten production efficiency or regulatory compliance. This reasoning is particularly relevant for the chemical industry, where production processes are often capital-intensive, technologically complex, and subject to extensive environmental and safety regulations. To examine this dimension, we classify all firms operating in the NACE (2-digit) sector "Manufacture of chemicals and chemical products" as belonging to a sensitive industry. Firms in this category represent 5.8% of our sample.

Second, we focus on the pharmaceutical industry. Innovation in the pharmaceutical sectors is characterized by very high R&D intensity, long development cycles, substantial regulatory requirements, and strong dependence on scientific knowledge and specialized human capital. At the same time, pharmaceutical production has increasingly attracted the attention of policy-makers because of its close relationship with public health security. Changes in input availability or input costs may therefore have particularly strong implications for firms' innovation strategies in this sector. We classify all firms operating in the NACE (2-digit) sector "Manufacture of basic pharmaceutical products and pharmaceutical preparations" as belonging to the health industry. These firms account for 2.0% of our sample.

Third, we examine industries that can be considered strategically important from the perspective of industrial policy and economic resilience. Recent research on global value chains and industrial policy has highlighted that certain manufacturing sectors play a central role in maintaining technological capabilities, supporting downstream production activities, and strengthening the resilience of the industrial base (Ding and Dafoe, 2021). Input trade shocks may therefore generate stronger innovation responses in these sectors, either because firms seek to reduce dependence on foreign suppliers or because governments actively support technological upgrading in strategically important activities. Following this rationale, we classify firms operating in the sectors "Manufacture of chemicals and chemical products", "Manufacture of basic metals", "Manufacture of electrical equipment", "Manufacture of motor vehicles, trailers and semi-trailers", and "Manufacture of other transport equipment" as belonging to strategic industries. Together, these sectors account for approximately 18.6% of the firms in our sample.

Finally, we consider sectors closely related to the defense industry. Defense-related sectors occupy a particular position because they combine high technological intensity, substantial public procurement, long-term government investment, significant geopolitical relevance with potential technological spillovers. Innovation in these industries is often shaped not only by market incentives but also by national security considerations and public support mechanisms. Moreover, concerns about supply-chain security and technological sovereignty may (directly or indirectly) strengthen firms' incentives to innovate when exposed to input trade shocks. We classify firms operating in the sectors "Manufacture of fabricated metal products, except machinery and equipment", "Manufacture of computer, electronic and optical products", and "Manufacture of other transport equipment" as belonging to defense-related industries. These sectors represent 23.0% of the firms included in our sample.

Table 5 presents estimates of Equation (9) for alternative measures of firms' patenting activity as dependent variables.

Our results reveal substantial heterogeneity across industries in the effect of input trade shocks on firms' innovation activities, suggesting that sector-specific technological and institutional characteristics play an important role in shaping firms' responses to changes in input market conditions.

We first examine sensitive industries characterized by stringent production constraints and regulatory requirements. The results indicate that input trade shocks reduce firms' propensity to innovate in technological domains directly related to the impacted products while simultaneously increasing innovation activity in domains indirectly connected to those products. The latter effect is sufficiently strong to amplify the aggregate innovation response. This pattern suggests that firms operating in highly constrained production environments may have limited scope to modify core technologies directly affected by the shock. Instead, they may try to redirect innovative efforts toward complementary activities located upstream or downstream in the value chain, such as process improvements, input substitution technologies, or the development of related products. More generally, the results are consistent with the view that high adjustment costs, strict regulatory requirements, and the capital-intensive nature of production limit direct technological adaptation while encouraging firms to seek alternative innovation pathways.

A different pattern emerges in the health sector. Our estimates reveal a negative effect of input trade shocks on the overall propensity to innovate, suggesting that such shocks reduce the likelihood that firms enter innovation activities. This finding is consistent with the specific characteristics of pharmaceutical production, which is associated with substantial sunk investments in research, clinical development, regulatory approval,

Table 5: Estimated effects of input price increase on patenting activity (industry-level heterogeneity)

	Total		Directly-linked		Indirectly-linked	
	Patenting	Number of patents	Patenting	Number of patents	Patenting	Number of patents
$\Delta \ln Z_{i,t}$	0.469	1.606*	0.757	-0.138	1.677**	1.452**
	(0.524)	(0.884)	(0.487)	(0.159)	(0.655)	(0.619)
$\Delta \ln Z_{i,t} \times \text{Sensitive}_{t_0}$	-0.252	-1.714	-2.466**	0.099	3.843**	0.168
	(1.974)	(1.953)	(1.159)	(0.317)	(1.548)	(0.961)
$\Delta \ln Z_{i,t}$	0.632	1.646*	0.610	-0.137	1.998***	1.465**
	(0.510)	(0.870)	(0.483)	(0.162)	(0.666)	(0.612)
$\Delta \ln Z_{i,t} \times \text{Health}_{t_0}$	-3.447**	-2.285	0.771	0.055	-3.024	-0.126
	(1.406)	(3.141)	(2.464)	(0.394)	(2.066)	(2.799)
$\Delta \ln Z_{i,t}$	0.347	1.412	0.107	-0.316**	1.229*	1.118*
	(0.593)	(0.976)	(0.493)	(0.154)	(0.716)	(0.637)
$\Delta \ln Z_{i,t} \times \text{Strategic}_{t_0}$	0.565	0.611	2.781**	0.938***	3.166***	1.750
	(1.027)	(1.840)	(1.204)	(0.343)	(1.033)	(1.502)
$\Delta \ln Z_{i,t}$	0.396	1.277	0.450	-0.114	2.058***	1.403**
	(0.604)	(0.934)	(0.542)	(0.130)	(0.736)	(0.714)
$\Delta \ln Z_{i,t} \times \text{Defense}_{t_0}$	0.277	1.139	0.894	-0.091	-0.956	0.251
	(1.048)	(2.129)	(1.136)	(0.470)	(1.521)	(1.202)
Controls	X	X	X	X	X	X
Year F.E.	X	X	X	X	X	X
Sector F.E.	X	X	X	X	X	X
Observations	7,911	7,911	7,911	7,911	7,911	7,911

Note: This table reports estimates of Equation (9) for alternative measures of firms' patenting activity as dependent variables: total patents, directly-linked patents, and indirectly-linked patents, and for alternative industry-level moderating variables. For each measure, the "patenting" column uses an indicator equal to one if the firm filed at least one patent application between t and $t+3$, while the "number of patents" column uses the logarithm of one plus the number of patent applications filed in the same period. Each specification is estimated separately for each moderating variable. Moderating variables are binary indicators equal to one if the firm belongs to the following industries: sensitive, health, strategic, defense. All specifications include the following predetermined (in t_0) firm-level controls: average sales, average workforce, average value added per worker, number of patent applications, sector fixed effects (NACE, 2-digit), and the import share of products with price-increase structural breaks and total import share, both interacted with year fixed effects. Estimates are obtained by OLS, with standard errors clustered at the firm level. Time period for t: 2016–2020. p-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

and specialized human capital. In industries where innovation projects require large irreversible investments and lengthy development horizons, disruptions in input markets may increase uncertainty and reduce the expected profitability of innovation projects. As a result, firms that have not yet entered innovation activities may postpone or abandon innovative investments following adverse input trade shocks. These findings suggest that the barriers to innovation entry are particularly important in highly knowledge-intensive and heavily regulated sectors.

The results for strategic industries point in the opposite direction. We find that input trade shocks increase both the probability that firms initiate innovation activities in technological domains directly related to affected products and the intensity of innovation within those domains. These positive effects reveal a composition pattern whereby the negative responses observed among non-strategic industries are offset by strong positive responses among strategic sectors. One interpretation is that firms operating in strategic industries have stronger incentives to reinforce technological capabilities in activities directly exposed to the shock. Rather than diversifying innovation efforts toward adjacent technologies, these firms appear to concentrate resources on strengthening the resilience, efficiency, and technological sophistication of the affected production segments. This interpretation is consistent with the recent debate on industrial policy, technological sovereignty, and supply-chain resilience in the European Union and the United States, which emphasize the importance of maintaining domestic capabilities in key industrial activities. Input trade shocks may therefore act as catalysts for innovation aimed at reducing technological dependencies and strengthening competitiveness within strategically important sectors.

Finally, we find no statistically significant differences in the innovation response of firms operating in defense-related industries. Although somewhat surprising given the strategic nature of these sectors, several explanations may account for this result. First, innovation in defense-related activities is often shaped by long-term procurement contracts, public funding programs, and government-defined technological priorities, which may insulate firms from short-term fluctuations in input markets. Second, innovation incentives in these industries are frequently driven by national security objectives rather than purely market-based considerations, potentially reducing the sensitivity of private innovative activity to input trade shocks. More generally, the absence of significant heterogeneity suggests that institutional arrangements and public-sector involvement may stabilize innovation efforts in defense-related sectors, thereby limiting the influence of changes in input trade conditions.

In summary, these findings indicate that the innovation response to input trade shocks depends critically on industry characteristics. Sectors characterized by high regulatory constraints tend to redirect innovation toward related technological domains, highly knowledge-intensive sectors experience weaker innovation entry, and strategically important industries strengthen innovation efforts in directly affected activities.

5 Conclusion

In this paper, we studied how imported input price shocks —– interpreted as negative supply shocks in foreign intermediate input markets —– affect both the intensity and the direction of firm-level innovation. Motivated by the growing fragmentation of global production networks and the increasing use of trade policy instruments that restrict access to key inputs, we asked whether such shocks merely depress innovative activity or whether they also induce a reallocation of inventive effort across products. Using rich French administrative data over 2014-–2023, we construct a firm-level measure of exposure to imported input price shocks based on structural breaks in product-level import unit values and a shift-share aggregation using predetermined sourcing patterns. To move beyond aggregate measures of innovation, we map patents to products using probabilistic concordance methods and embed these products within production networks, allowing us to trace not only whether firms innovate more or less, but also where in the technological space this innovation takes place. Our approach is novel along several dimensions. First, we bridge macroeconomic shocks and microeconomic responses by decomposing the effects of geopolitical transformations at a highly granular level, thereby linking aggregate trade disruptions to firm-level adjustments in innovation. Second, unlike much of the existing literature that focuses on specific countries, products, or episodes, we systematically map input-price shocks across all country–product pairs, providing a comprehensive view of global supply disruptions. Third, we connect the literature on trade and innovation by examining how firms adjust not only the intensity but also the direction of innovation in response to changes in imported input costs — a margin that has been relatively underexplored.

Our main findings can be summarized in three points. First, imported input price shocks do not primarily operate through a reduction in overall innovative activity. Aggregate patenting responds only modestly, and in some specifications even increases slightly. Second, and more importantly, firms do not redirect innovation toward directly impacted products. Instead, innovation is systematically reallocated toward technologically and economically related domains —– inputs that are connected through upstream, downstream, or adjacency relationships in the production network. This pattern is consistent with a network-based form of technological adjustment in which firms respond to input constraints by innovating in substitute or complementary technological spaces rather than directly within the constrained input category. Third, these responses are highly heterogeneous. Firms closer to the technological frontier exhibit stronger and more systematic reallocation of innovation across related technological domains, consistent with greater absorptive capacity and flexibility in their innovation portfolios. By contrast, smaller and less productive firms adjust more along the extensive margin of innovation. Sectoral differences are also pronounced, with regulated industries and strategic sectors displaying distinct patterns of reallocation and within-domain innovation responses. Taken together, these results suggest that negative input supply shocks reshape innovation primarily through a compositional margin rather than through a pure scale effect.

From a broader perspective, our findings have implications for understanding the long-run consequences of geopolitical risk and global value chain disruptions. If firms systematically redirect innovation toward technologies that reduce exposure to constrained inputs, then trade fragmentation may not only alter current production patterns but also reshape the future technological frontier. At the same time, the heterogeneous nature of these responses suggests that such adaptive mechanisms are likely to reinforce differences in innovation capacity across firms and sectors, with potential implications for aggregate productivity dynamics and industrial structure. Several avenues remain open for future research. First, while this paper documents robust reallocation patterns in patenting activity, further work could explore whether these shifts translate into measurable productivity gains or changes in production technologies. Second, understanding the welfare implications of defensive innovation requires a better characterization of whether such reallocation leads to efficient substitution or to fragmented and redundant innovation efforts. Finally, extending this framework to other countries and institutional environments would help increase the external validity of these mechanisms and their relevance in different stages of development and industrial structure.

In summary, we showed that innovation constitutes a key margin of adjustment to trade fragmentation. Imported input price shocks do not only affect how much firms innovate, but also how they innovate. In an era of increasing trade fragmentation, this distinction is central to understanding how global shocks propagate into the evolution of technology and, ultimately, long-run economic growth.

Competing interests declaration

Competing interests: The authors declare none.

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A Appendix

A.1 Pre-trend tests

Table A1: Estimated effects of input price increase on innovation activity (pre-trend test)

	Lagged total		Lagged directly-linked		Lagged indirectly-linked	
	Patenting	Number of patents	Patenting	Number of patents	Patenting	Number of patents
$\Delta \ln Z_{i,t}$	-0.234	-0.732	0.310	0.134	0.670	0.190
	(0.357)	(0.440)	(0.361)	(0.121)	(0.562)	(0.414)
Controls	X	X	X	X	X	X
Year F.E.	X	X	X	X	X	X
Sector F.E.	X	X	X	X	X	X
Observations	7,826	7,826	7,826	7,826	7,826	7,826
R^2	0.02	0.03	0.14	0.18	0.15	0.13

Note: This table reports estimates of Equation (8) for alternative measures of firms' lagged patenting activity as dependent variables: total patents, directly-linked patents, and indirectly-linked patents. For each measure, the "patenting" column uses an indicator equal to one if the firm filed at least one patent application between $t-4$ and $t-1$, while the "number of patents" column uses the logarithm of one plus the number of patent applications filed in the same period. All specifications include the following pre-determined (in t_0) firm-level controls: average sales, average workforce, average value added per worker, number of patent applications, sector fixed effects (NACE, 2-digit), and the import share of products with price-increase structural breaks and total import share, both interacted with year fixed effects. Estimates are obtained by OLS, with standard errors clustered at the firm level. Time period for t: 2019–2023. p-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.