Acquiring Supplier Networks: Domestic Mergers for International Supply Chain Resilience

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Long-standing international supplier relationships represent valuable and hard-to-replicate intangible assets that mitigate the search and contracting frictions inherent in global value chains. We propose and show that domestic mergers and acquisitions (M&A) serve as a key strategic vehicle for acquiring these established supplier networks, providing a novel source of merger synergy. Using detailed transaction-level shipment data from 2007–2020, we find that post-merger, acquirers systematically adopt the target's supplier relationships, with a pronounced preference for those that are long-standing. This adoption occurs for both inputs the acquirer already sources (enhancing resilience) and new inputs (facilitating expansion). Consistent with this type of synergy, the likelihood of a merger increases with the similarity of the firms' imported input portfolios, especially during periods of heightened supply-chain risk, when the value of a target's vetted network is highest. Furthermore, these mergers generate competitive advantages through foreclosure-like effects on target rivals when their supply chains overlap with the acquirer's, leading to improved valuations and sales growth for target firms. Overall, we show that a primary synergy in many M&As is the acquisition of "relational capital" embedded in the target's supply chain.

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1. Introduction

Trade in intermediate inputs constitutes as much as two-thirds of world trade (Johnson and Noguera, 2012; Antràs and Chor, 2021). This dominant feature of the modern global economy—the rise of Global Value Chains (GVCs)—is the result of a profound transformation driven by the information and communication technology revolution, which lowered coordination costs; a sharp reduction in trade barriers that made production fragmentation more viable; and political changes that expanded the global marketplace (Antràs, 2016).

While this slicing up of the production process offers firms significant efficiency gains, it also exposes them to substantial frictions. As documented by Antràs and Chor (2021), GVCs present many challenges, including the high costs of searching for suitable international partners, the contractual insecurities that arise from relationship-specific investments, and weak cross-border legal enforcement. In this environment, firms cannot rely on formal contracts alone. Instead, they often depend on *relational* contracting, where the prospect of continued future business fosters trust and cooperation. These long-term, stable buyer-supplier relationships are therefore valuable intangible assets that are costly and time-consuming to build from scratch.

As they expand their global operations across multiple margins—choosing which products to make, which markets to export to, and which inputs to import from which countries (Bernard et al., 2018)—firms are constantly seeking to optimize their international supply chains, either to build resilience or to facilitate expansion. However, the search for new international suppliers is hampered by the very frictions—high search costs and contractual hazards—that make existing, long-term relationships so valuable.

In this paper, we propose and provide evidence for a novel channel through which firms can circumvent these frictions: domestic mergers and acquisitions (M&A) as a vehicle for acquiring and realigning international supply chains. Rather than incurring the search frictions inherent in building new international relationships with suppliers, or pursuing complex cross-border vertical mergers, a firm engaged in a domestic acquisition activity can inherit the target's entire network of established international supplier relationships. This type of merger—which we term *Import Related Mergers* or *IRM*s— is particularly attractive to domestic firms for two reasons.

First, an acquirer can enhance the resilience of its existing international supply chain. Resilience has emerged as a critical concern, with studies indicating that U.S. companies face significant disruptions every few years, leading to expected losses over a decade equivalent to 42% of annual pre-tax earnings (McKinsey Global Institute, 2020). Firms often discuss supply chain risks in earnings conference calls (Ersahin, Giannetti, and Huang, 2024). Finding reliable alternatives, however, is impeded by the same search and contracting frictions that make established partnerships so valuable in the first place. By acquiring a domestic target that imports a similar portfolio of inputs, the acquirer gains immediate access to a pre-vetted, alternative set of suppliers, dramatically lowering its search costs and mitigating disruption risks.

Second, an acquirer can use M&A to bypass the costs of establishing new relationships with suppliers and expand its supply chain into new inputs. This motive is crucial for firms looking to develop new product lines, lower production costs, or enter new markets (Bernard et al., 2018). Rather than building new international supplier relationships from scratch, a firm can acquire a target and inherit its established network for inputs it does not currently source.

Using a merger to acquire a target's supply-chain relationships offers several distinct advantages over contracting with new suppliers directly or pursuing other strategies like vertical mergers. The due diligence process in an M&A deal reveals rich information about the quality and reliability of the target's suppliers, leveraging the target's own experience. Furthermore, retaining target personnel who possess a history of interaction with these suppliers transfers valuable human capital and tacit knowledge, ensuring supply continuity. When the scale of restructuring is large, a merger allows the acquirer to inherit multiple relationships in a single, efficient transaction. This approach is also distinct from a vertical merger; while acquiring a single upstream firm secures one supply line, an *IRM* can provide access to multiple alternative suppliers for the same input, offering superior diversification and resilience.

Managers sometimes explicitly mention the supply chain-related motives behind mergers, although, it is more common for them not to directly mention supply chain issues but rather talk about "synergies", "operational efficiencies", or "broadened capabilities" etc. An exception is the 2021 merger of American Eagle Outfitters and Quiet Logistics. Jay Schottenstein, American Eagle's executive chairman and CEO said in a statement after the $350 million deal was announced, "An important pillar of our strategy is transforming our supply chain to create greater agility, speed, and diversification." [1] As another example, in the merger of LVMH and Tiffany, the CEO of LVMH stated "Tiffany is a very big player in all sorts of diamonds, and it's something where the sourcing is not easy to do, and we expect to benefit from that." [2]

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[1] See "Companies Build Supply Chain Resilience Through Mergers and Acquisitions: M&A is filling Supply Chain Gaps", by D. Adamek, here.

[2] During the merger of LVMH and Tiffany, Tiffany's unique sourcing strategy played a crucial role. Unlike many competitors, Tiffany procured rough diamonds directly from mines and handled the cutting process in-house, rather than purchasing from wholesalers. This approach not only ensured greater control over quality but also provided LVMH's jewelry business with critical access to these key suppliers.

In our empirical analysis, we find evidence of both of the above motives for *IRM*s. To construct our sample of *IRM*s, we begin by identifying mergers between firms that have import records in Standard and Poor's *Panjiva* database.[3] Our acquirers are publicly traded firms while the targets can be either public or private targets. We then create cohorts for each merging pair by selecting five non-merging firms from the acquirers' and targets' industries, respectively, that are closest in terms of import volume, and creating "placebo-pairs", which serve as the control pairs. For each pair, we create an *imported input similarity score* (henceforth, *IIS*) based on their import records in *Panjiva*, which is a cosine similarity score between their respective imported input vectors. We then examine whether a merger between a pair is more likely if the pair enjoyed a higher *IIS*. The purpose behind this test is to see whether targets are more attractive when they import similar inputs as the acquirer, in which case the merger gives the latter access to alternative sources of supply, as long as they are not importing from the same suppliers. To tease out the incremental effect of *IIS*, in our regressions, we control for similarity scores based on supplier similarity, [4] as well as the similarity of the country of origin of the imports, between the acquirer and the target.

We find that the imported input similarity score is strongly and positively related to the probability of a pair being involved in a future merger. A natural concern here is that imported input similarity may be related to product similarity. For public targets, we include the Hoberg-Phillips product similarity score (Hoberg and Philips, 2016). While the product similarity score

[3] This choice of restricting attention to firms with available import records is dictated by the need to study how the acquirer's sourcing behavior changes following the merger.
[4] Supplier similarity is the cosine similarity between vectors—one for the acquirer and one for the target— where each element of the vector represents a supplier in the database, and is assigned a value of 1 if the firm imports from that supplier, and zero otherwise.

itself is significant, its inclusion has a minor effect on the coefficient of the imported input similarity measure.

These results point to an important motive for *IRM*s, namely, to inherit from the target alternative suppliers for the same inputs that an acquirer already imports, and enhance supply chain reliance. Such an incentive should be stronger when the acquirer faces higher supply chain uncertainty. Using the firm-specific supply chain risk perception measure developed by Ersahin et al. (2024), we indeed find that an increase in imported input similarity leads to a higher likelihood of a merger involving a public target when supply chain risk perception is higher. However, we do not find significant results for the full sample of mergers which also includes private targets. We conjecture that acquiring the larger public targets with many suppliers provides alternative sources of supply quickly when supply chain uncertainty increases, compared to acquiring private targets; however, acquisitions of private targets are more routine efforts to develop more robust supply chains for the longer term. We find similar results when we include (i) an economy-wide supply chain risk measure borrowed from Ersahin et al. (2024), and (ii) trade policy uncertainty, in place of firm-level supply chain risk.[5]

Interestingly, about half of our sample *IRM*s occur between pairs with zero *IIS*. Since the similarity measure is based on imported inputs, it is possible that these acquirers source inputs domestically, and want to strengthen their supply chains by reducing their dependence on domestic suppliers.[6] However, we find that the coefficients of the standalone supply chain risk perception

[5] Trade policy uncertainty is likely disruptive for the supply chains of our sample firms and increases uncertainty about the cost of imported inputs.
[6] Information on domestic input purchases for U.S. firms is not readily available.

measures (which capture the effect of risk perception for acquirers in zero *IIS* deals) are not significant in our regressions.

We find evidence consistent with theories that suggest that firms' trading activities (export and import volume, the number of products or destinations they export from or import to), are interdependent and complementary (Bernard et al., 2018). For both the subgroups with *IIS*>0 and *IIS*=0, we find that previous (alternatively, the current) period's sales to non-U.S. countries, the number of products exported, and the number of destinations the firm exports to, strongly predict the likelihood of an *IRM*. Essentially, these variables proxy for shocks that make it profitable to expand trade across all the different margins. For example, as firms export to new destinations and sell more products, they need more reliability in the supply chain for their core inputs and also need to identify suppliers for new inputs. The expansion in production scale makes it worthwhile to pay for the fixed costs of acquiring these new inputs. The *IRM*s are one channel through which these needs are met.

Acquirers face significant challenges in identifying suitable domestic targets that possess desirable international supply chain resources in *IRM*s, primarily due to a lack of required supplier-related information disclosure. We find that acquirers circumvent this information barrier through two channels: recruiting former employees of the target firm with supply-chain expertise, or employing data analysts who are capable of leveraging publicly available or third-party proprietary data. Our findings suggest that the likelihood of such an acquisition is significantly higher when the acquirer has either recruited supply-chain experts from the target or employs more data analysts before the deal announcement, especially when the two firms have positive imported input similarity. Our results confirm that these channels are crucial for reducing acquirers' information costs associated with identifying valuable international supply chain networks in *IRMs*.

We next leverage the granular *Panjiva* data and proceed to provide evidence that both acquirers in positive *IIS* deals, as well as those involved in zero *IIS* deals, buy new inputs after the merger from target suppliers, and especially from those suppliers with longer relationships with the target than their placebo counterparts. Of course, the positive *IIS* group show a stronger inclination to buy inputs it already imports from other sources, consistent with the idea that increasing supply-chain resilience and finding *alternative* suppliers is a strong motive.[7] This is our strongest evidence that an important part of the synergy gains from these mergers come from the access to target's suppliers that the deals make possible for the acquirer.

Apart from providing the granular information on the imported products, an important advantage of the *Panjiva* database is that it provides the consignee names for each shipment. For the tests described below, we report our results for a "restricted" sample of mergers that requires all pre-event target consignee names to be active in importing from international suppliers after the merger event, which makes it unlikely that target units' operations are integrated within the acquirer's units. By focusing on the acquirer consignees that were active before the merger, we can examine whether the sourcing characteristics of the pre-merger acquirer entities changed.

To begin with, we show that in the three years after the merger, compared to the acquirers in placebo deals, the acquirers in the actual deal add more new suppliers and import from a larger number of countries. Both effects are present for the sample of positive *IIS* as well as the sample of zero *IIS*. Moreover, the former effect is stronger for the sample of positive *IIS* deals than for the sample of zero *IIS* deals. To test the robustness of our results, we also identify a sample of withdrawn *IRM*s to identify counterfactuals, and match these deals to completed deals (Savor and

[7] In fact, acquirers are more likely to discontinue existing relationships with supplier after the merger. This provides additional evidence that the mergers are associated with a restructuring of the acquirer's international supply chain.

Lu, 2009; Bena and Li, 2014). We find consistent results: the number of new suppliers increases post-merger for the completed deals, and this effect is stronger when *IIS* is higher.

We next focus on how the importing behavior of the acquirer units changes after the merger. This analysis is conducted in a stacked difference-in-differences setting with deal cohort×target-supplier×acquirer fixed effects and deal cohort×year fixed effects. First, we find that the actual (i.e., treated) acquirer is more likely to purchase from a target supplier that it did not purchase from before, and this is the case both for inputs it was already purchasing (from its own suppliers prior to the deal) as well as new inputs.[8] Moreover, while these effects are significant for both the sample of positive *IIS* and zero *IIS* deals, all of these effects are stronger for the former, which suggests that the target becomes more attractive the greater the overlap of imported inputs. These results thus provide granular evidence that the acquisition enables the acquirer to change the sourcing of its inputs for its production processes.

Second, and importantly, we find that the likelihood of buying from a target supplier is twice as high when the target's experience with the supplier is three years (the sample mean rounded to the nearest whole number) or more, than when it is less than three years. The importance of the length of the target's experience with a supplier is consistent with the idea that the parties learn more about each other and develop trust the longer the relationship continues. Finally, we also find that the target (i.e., the units not merged with the acquirer) are also more likely to buy inputs from the acquirer's supplier it did not buy from its own suppliers before, although the magnitude of this effect is small.

[8] We find similar results for the sample of matched withdrawn mergers: the acquirer in a completed deal buys more from the target's suppliers than the acquirer in a counterfactual cancelled deal does from the intended target in the post-deal years.

We also investigate the real effects of *IRM*s on labor market outcomes, specifically testing whether the strategic motive to acquire targets' international supply chain networks creates a strong incentive for acquirers to retain the target's supply-chain-related talents. This test is built upon the well-established finding that the strength of relational contracts between two firms heavily relies on the long-term and repeated relationship-specific human capital investment of employees (e.g., Williamson, 1985; Baker, Gibbons, and Murphy, 2002). Using employee-level career history data from the Revelio Lab, we find that target employees with supply-chain expertise are significantly more likely to be retained by the acquirer following an *IRM*. This retention effect is unique to long-tenured employees and robust across different time horizons. This finding supports our conjecture that the relationship-specific knowledge and connections of target employees, accumulated in long-term bonding with their international suppliers, are crucial relational assets that acquirers must retain to realize the synergies of *IRMs*.

Together, these results suggest that the main attraction of the target for the acquirer is not simply the list of suppliers it has relationships with (although that information is important for the acquirer to identify a target),[9] but the relationships themselves. These relationships are built through repeated transactions, based on larger volumes of transactions over time, as implied by models of relational contracting (Antràs and Foley, 2015; Araujo et al., 2016; Monarch and Schmidt-Eisenlohr, 2017).[10] A distinguishing feature of this line of models is that they naturally

[9] The international supplier information, sourced its U.S. import and export data from the U.S. Customs and Border Protection (CBP) through the Automated Commercial Environment (ACE) and Bill of Lading (BoL) filings, has been publicly available since 2006.

[10] While simple adverse selection models might suggest a long-term relationship provides a public signal of supplier quality, this is not the case when the value of such relationships is dyadic and private. This can be due to the need for two-sided trust (Macchiavello & Morjaria, 2015), the establishment of a self-enforcing relational contract (Baker et al., 2002; Antràs & Staiger, 2012), or the creation of match-specific, non-transferable productivity through joint learning (Rauch & Watson, 2003; Eaton et al., 2011).

generate an increasing volume of trade as relationship age increases.[11] An acquirer bypassing the target and seeking to enter into a new relationship with the supplier would necessarily have to start with a low volume of transactions initially; in contrast, through the acquisition, it immediately inherits an asset (the relationship) that, other things unchanged, is in neither party's interest to break. In addition, the combined purchases from the target and the acquirer give the supplier a strong incentive to be flexible vis-à-vis a more important customer and preserve the relationship. Finally, the personal knowledge and tacit experience of the target's personnel regarding the supplier represent additional valuable human capital that is transferred through the acquisition and add to the synergy created by the deal.

While the synergy from acquiring supplier relationships is likely to be one of the main motivations of *IRM*s, we also find an effect of these supply chain-guided mergers that are very similar to what has been recently documented in the context of vertical mergers. A long—mostly theoretical—literature in Economics posits that the vertical integration of an upstream supplier with a downstream customer might "foreclose" the access of competing downstream firms to an important input, a phenomenon termed "vertical foreclosure" (Salinger, 1988; Hart and Tirole, 1990; Ordover, Saloner, and Salop, 1990). Empirical evidence, however, has been limited to a few case studies. Recently, Boehm and Sonntag (2023) provide evidence that foreclosure outcomes are in fact quite common following vertical integration.

For the mergers in our sample, we find foreclosure-like outcomes. The reason for such outcomes is also related to the contracting costs of establishing new relationships for the

[11] For example, both parties may increase relation-specific investment when they update their priors that the other is a "good type", enlarging the "surplus". A longer relationship, in turn, can generate a higher surplus in the future as the parties learn to work together, enlarging the value of continuation, thereby making cooperation even easier to sustain, and allowing for even higher levels of joint investment (MacLeod and Malcolmson, 1989; Levin, 2003; Board, 2011).

competitors of the target, when their supply chains overlap with the acquirers'. Specifically, we establish the following results (which are limited to public targets because we need to identify the target's competitors). First, the merger is more likely if the overlap between the acquirer's suppliers and those of the target's *competitors'* is greater, and this effect is stronger if the acquirer's suppliers on average have longer relationships with the acquirer than the target's rivals. Second, the number of the target's rivals that import from the acquirer's suppliers, and the likelihood of a rival importing from a supplier of the acquirer, decrease post-merger. Finally, for targets that remain publicly listed, we observe increases in the market-to-book ratio and sales growth post-merger. Even though the mergers in our sample are not necessarily vertical mergers, these results point to potential merger synergies that stem from the acquirer's ability to restrict the access of the target's rivals to its longer-term suppliers.

Concern about supply chain resilience has driven recent research on network fragility and firm responses to disruptions. Theories of network formation highlight the inherent fragility of supply chains and the transmission of shocks (e.g., Bimpikis, Fearing, and Tahbaz-Salehi, 2018; Elliott, Golub, and Leduk, 2022; Kopytov, Mishra, Nimark, and Taschereau-Dumouchel, 2024). Empirical studies document firm responses to elevated supply chain uncertainty. Jin, Liu, and Tian (2024) examine how geopolitical risk reshapes supply chains, while Ersahin et al. (2024) use textual analysis of earnings calls to measure supply chain risk and sentiment, and study how firms deal with elevated supply chain risk. We make several contributions to this literature. First, we identify a new rationale for mergers, especially likely for firms facing supply chain risk and seeking to strengthen the resilience of their supply chains, that are not necessarily between vertically related firms, but nonetheless, are consequential for supply chain realignment. As noted, while we examine this issue through the lens of mergers between firms that are both importers, the issue is likely broader and should extend to mergers between firms that rely entirely on domestic inputs. We additionally add to the recent empirical literature on corporate strategies to boost supply chain resilience (Esrahin et al., 2024 and Jin et al., 2024). Finally, we add to the literature on vertical foreclosures by showing that there is also a foreclosure element associated with the *IRMs*, which boost the target's sales performance and market value.[12]

The rest of the paper is organized as follows. Section 2 presents our data sources and provides summary statistics. Section 3 discusses how domestic M&A deals can help acquirers make international supply chains more resilient. Section 4 investigates vertical foreclosure as another possible motive of supply-chain-driven deals. Section 5 concludes.

2. Data Sources and Summary Statistics

2.1 Import Records Data

We obtain import records of US firms from Standard and Poor's Panjiva database. The data cover all sea-based imports, derived from mandatory filings that U.S. firms are required to submit to U.S. Customs and Border Protection (CBP) for physical shipments. The data capture detailed shipment information, including the names and addresses of the US importers and the international exporters, shipment origin, arrival date, product types (Harmonized System (HS) product codes), and quantities.

[12] Another recent literature (that sometimes uses the *Panjiva* data) examines some other aspects of sourcing: (i) how firms' international sourcing behavior is affected by the managers' political ideology (Ayyagari, Gao, and Ma, 2025; Kempt, Luo, and Tsoutsoura, 2025), a firm's pollical leaning (Charoenwong, Peng, and Wu, 2025), and economic sanctions (Bei, Qi, Wu, and Zhou, 2025).

We define product categories using the six-digit HS code, which offers a granular classification of traded goods. This level of detail ensures that when two firms import goods under the same six-digit HS code, the goods are highly comparable, allowing for accurate measurement of imported input similarity between firm pairs. For instance, HS code 8518.21 refers specifically to “Single loudspeakers, mounted in their enclosures,” while HS code 8518.22 covers “Multiple loudspeakers, mounted in the same enclosure.” Both codes refer to loudspeakers already mounted in enclosures—intermediate goods commonly used in the production of audio equipment. The only distinction between these two codes is whether the enclosure contains a single loudspeaker or multiple loudspeakers. The level of detail captured by the six-digit HS code system enables precise measurement of imported input similarity across firms.

2.2 Mergers and Acquisitions Data and Sample Construction

Our M&A data is drawn from the Securities Data Company’s (SDC) Mergers and Acquisitions Database. We match acquirers and targets in SDC to consignees in the Panjiva database using a name-matching algorithm. Each matched pair is manually verified to confirm its accuracy and reliability.

To construct our sample, we impose the following sample selection criteria: (1) the deal must be classified as a merger, acquisition of majority interest, or acquisition of assets; (2) the transaction value must exceed $1 million USD; (3) the acquirer must hold less than 50% of the target’s shares prior to the deal and hold a majority stake (more than 50%) as a result of the transaction; (4) we exclude deals involving firms in the financial sector (SIC 6000–6999); (5) the acquirer must be a US publicly listed firm; and (6) both the acquirer and the target must have records of import activities in the *Panjiva* database, where data availability is from 2007 onwards, in the year prior to the deal announcement.

After applying these screening criteria, we get 1,137 unique deals for the 2007-2021 sample period. To construct a control sample, we create a pool of potential merger participants by matching firms based on industry and import volume. Specifically, for each deal participant (acquirer or target) in a transaction announced in year *t*, we identify up to five firms from the same three-digit SIC industry with the closest total import volumes in year *t-1*, using data from Panjiva. These firms must not have participated in any M&A deals as either acquirers or targets during our sample period. We require only acquirers to be public firms when filtering the sample; targets may be either public or private. Accordingly, we match public targets to public control firms and private targets to private consignees from Panjiva. As SIC codes are often missing for private firms, we rely on Panjiva's own industry classification variable (*simpleindustryid*) to assign industry categories when matching control firms for private targets.

To construct the placebo deals, we match each actual target with up to five placebo acquirers that are matched to the actual acquirers based on industry and import volume. Likewise, each actual acquirer is matched with up to five placebo targets using the same criteria. This procedure yields up to ten placebo deals per actual transaction, consisting of both actual acquirer–placebo target and placebo acquirer–actual target pairs. Our final sample includes all actual deals along with their corresponding placebo counterparts.

2.3 Imported Input Similarity (IIS) Measure

To assess the extent to which merging firms import similar goods, we construct a pairwise measure of imported input similarity using detailed shipment-level import data. For each firm in the pair—acquirer *i* and target *j*—we define an import vector based on six-digit Harmonized System (HS) product categories. For example, for acquirer *i* in year *t*, the import vector is given by:

$$V_{i,t} = [Volume_{i,h1,t}, Volume_{i,h2,t}, Volume_{i,h3,t}, \dots, Volume_{i,hn,t}]$$

where $Volume_{i,h_k,t}$ denotes the volume of product h_k imported by firm *i* in year *t*. If the firm does not import a particular product, the corresponding entry is set to zero.

We compute the imported input similarity (*IIS*) between an acquirer-target pair as the cosine similarity between their respective import vectors:

$$IIS_{i,j,t} = \frac{V_{i,t} \cdot V_{j,t}}{|V_{i,t}||V_{j,t}|}$$

This measure captures the degree of overlap in the composition of imported inputs between the acquirer and target firms. This measure ranges from 0 (no overlap in imported inputs) to 1 (perfect alignment), with higher values indicating higher similarity in internationally sourced goods. By using six-digit HS codes, we ensure sufficient granularity so that any observed overlap reflects meaningful similarity in input types, rather than simply broad product categories.

3. Domestic Acquisitions to Diversify International Supplier Base

3.1. Baseline Results

To examine whether imported input similarity is positively correlated with the likelihood of mergers, we construct our testing sample at the acquirer-target-year level, following a methodology similar to Bena and Li (2014). First, we identify all acquirer-target pairs during our sample period. Throughout the paper, we refer to these firms as *actual acquirers* and *actual targets*. We refer to these M&A deals as *actual deals*. Second, for each actual acquirer in a given deal, we match it with five firms within the same three-digit SIC industry as the actual target, selecting those with the smallest differences in terms of import volume from the actual target. We refer to these matched firms as *placebo targets*. Similarly, for each actual target, we pair it with five *placebo acquirers* using the same matching criteria. We refer to pairs between actual (placebo) acquirers and placebo (actual) targets as *placebo deals*. Finally, an actual deal and its corresponding placebo deals, combined together, are collectively referred to as a *cohort*. We combine all cohorts to form the final testing sample. The test specification is outlined in Equation (1) below:

$$True_{i,j,t} = IIS_{i,j,t} + Supplier\ Similarity_{i,j,t} + Product\ Similarity_{i,j,t} + Acquirer\ Controls_{i,t} + Cohort\ FE \tag{1}$$

where *i* denotes the acquirer, *j* the target, and *t* the deal announcement year. The dependent variable, *True*, is a binary indicator that equals one for actual acquirer-target pairs and zero for pairs involving placebo acquirers or targets. The key independent variables are defined as follows. *IIS* measures the cosine similarity of input products between the acquirer and target, as defined in Section 2.3. *Supplier Similarity* captures the cosine similarity of the international supplier base shared by the acquirer and target. *Product Similarity* is constructed using the Hoberg-Phillips TNIC3 product similarity score. We also control firm characteristics of acquirers, including the natural logarithm of total assets (*LogAsset*), book leverage (*Leverage*), capital expenditure scaled by total assets (*Capex*), cash holdings scaled by total assets (*Cash*), dividend payout ratio (*Dividend*), Tobin's Q (*TobinQ*), and return on assets (*ROA*). Definitions of all dependent and independent variables are provided in Appendix I. We include cohort fixed effects in all test specifications to control for market-wide economic shocks that may influence all firms around the time of deal announcements. This specification ensures that our identification comes from within-cohort comparisons between actual acquirer-target pairs and their corresponding placebo pairs. We cluster standard errors at the deal-cohort level to account for potential residual correlation across observations.

[Insert Table 2 Here]

Columns (1) and (2) of Panel A in Table 2 present results based on the full sample, which includes deals involving both public and private targets. Our findings indicate that *IIS* is positively associated with the likelihood of mergers and acquisitions, with statistical significance at the 1% level. The coefficient of 0.255 in column (2) implies that a one-standard-deviation increase in *IIS* raises the probability of M&As by 3.19 percentage points, equivalent to a 28.2% increase relative to the sample mean. Columns (3) to (5) report estimates from a subsample restricted to public targets. Here, the coefficients for *IIS* are slightly smaller than those in the full sample, suggesting that this factor plays a more pronounced role in deals involving private targets.

We also find that other similarities—such as supplier and product overlaps—are positively correlated with M&A likelihood.[13] However, controlling for these similarities does not diminish the economic or statistical significance of imported input similarity in our baseline tests. This result implies that imported input similarity captures a distinct dimension of M&A motivations, orthogonal to the economic rationales reflected by other similarity measures.

In Panel B of Table 2, we introduce another measure of imported input similarity, and include it as an independent variable alongside *IIS*. This measure, which we label *industry imported input similarity (Industry IIS)*, is the average similarity between the target's (or the placebo target's) import profile and that of same-industry peer firms of the acquirer. This variable is intended to capture the similarity of the target's import profile and a hypothetical import profile that the acquirer could potentially be interested in importing. For example, it could be the case that the acquirer currently sources certain inputs domestically, whereas some of the rivals import them. Consistent with our conjecture, the *Industry IIS* measure is positively correlated with the M&A

[13] The significance of supplier similarity disappears once product similarity is controlled for. This suggests that it might be related to product similarity. The significance of product similarity is consistent with motives related to market power or other types of synergies between firms producing related products.

likelihood in most test specifications (except column (5)). However, the coefficients of *IIS* remain statistically and economically significant after controlling for *Industry IIS*.

The trade war between the U.S. and China in 2018-2019, along with COVID-19-related disruptions, heightened awareness of supply chain vulnerabilities among US firms with significant exposure to China. In Panel C, we examine whether the trend of "diversifying out of China" gained momentum after 2020. To do so, we replace *IIS* with a new similarity variable, which is the cosine similarity of the acquirer's inputs imported from China and those of the target that are *not imported* from China (*China IIS*). In other words, when this similarity score (which is in fact a dis-similarity score in terms of China exposure) is higher, the target is more attractive to an acquirer seeking to reduce exposure to China. We find that *China IIS* itself has a significant positive coefficient in all columns, suggesting that "diversifying out of China" has been in effect for the entire sample period. However, for public targets, the interaction of *China IIS* and *Post*, which is a dummy variable taking the value of 1 (0) for years after (before) 2020 is positive and highly significant, suggesting that post-2020, acquiring public targets importing from countries other than China is likely to be an important avenue for diversifying out of China. This is consistent with the perception that after COVID-19 and the associated supply chain disruptions, "many companies realized they needed more visibility into their supply chains and scrambled to remedy longstanding supply chain issues."[14]

3.2. Exogenous Variations of International Supply-Chain Risks

Our results so far that *IIS* is positively related to the likelihood of a merger are subject to omitted variable bias. Firms with similar input profiles could be similar in many other respects,

[14] "How do Mergers and Acquisitions Impact Supply Chains?", at this link.

such as technology, human capital profiles, and so on. So far, we have attempted to address this concern by comparing the actual deals with placebo deals between firms drawn from the same industry and similar in their reliance on imports, and including cohort fixed effects. To provide more convincing evidence that firms acquire domestic peers with similar imported inputs to strengthen their international supply sources, we leverage exogenous variations in international supply-chain risks—factors beyond the influence of individual corporate decisions. If, as we argue, the primary motivation for these acquisitions is indeed to enhance supply-chain resilience through supplier diversification, we should observe a more pronounced baseline effect during periods of heightened global supply-chain risks or uncertainties.

We borrow three measures of global supply-chain risks or uncertainties from previous studies for this test: Acquirer-specific supply chain risks (Ersahin et al., 2024) and economy-wide supply chain risks (the average supply chain risk in a given year) from the same source, and the trade policy uncertainty measure in Caldara, Iacoviello, Molligo, Prestipino, and Raffo (2020). While the first of these measures is firm-specific and could be still correlated with omitted variables, it has the advantage of being based on firms' own stated concerns about supply chain risk in earnings conference calls (Ersahin et al., 2024). The second and third measures, arguably, are more exogenous in nature. We augment the baseline test specifications by interaction terms between *IIS* and one of the supply-chain risk/trade policy uncertainty measures. Results are reported in Table 3.

[Insert Table 3 Here]

The results in Table 3 indicate that the coefficients for the interaction terms between *IIS* and alternative supply-chain risk measures are positive and statistically significant—but only within the subsample of M&A deals involving public target firms. For the subsample with public targets, the relationship between *IIS* and M&A probability strengthens under heightened international supply-chain risks or uncertainties. This pattern, however, does not extend to the full sample when private targets are also included. One plausible explanation for this divergence is that acquiring larger targets when supply chain risk is high provides access to a larger number of target suppliers relatively quickly, compared to acquiring smaller private targets. Moreover, elevated supply-chain risks may justify the higher due diligence costs and protracted negotiation processes typically associated with acquiring public targets, as these deals are often motivated by the need for immediate risk mitigation. In contrast, acquisitions of private targets may reflect more routine, long-term strategies aimed at building resilient supply chains rather than responding to short-term disruptions.

3.3 Acquirer-Target Industry Heterogeneity

Even though we control for the product similarity score in our regressions, there could be some concern that we are picking our horizontal relatedness via our *IIS* measure. About 40% of the deals in our sample involve acquirers and targets within the same 3-digit SIC industry.[15] In Panel A of Appendix Table A1, we report results similar to those in Panel A of Table 2, for acquirer-target pairs in the same industry (Columns (1) and (3)) and in different industries (Columns (2) and (4)). When all deals are considered, *IIS* has a significantly positive coefficient in both subsamples, and the coefficient is about 50 percent larger for mergers in which the merging entities are from different industries. However, for public deals only, while the coefficient

[15] There is little evidence that the remaining deals are vertically related. To determine likely vertical relatedness, we identify customer-supplier relationships from the *Factset Revere* database. Among these remaining deals, 22% occur between firms in industries that show no customer-supplier relationships between them, indicating very low likelihood of vertical relatedness. While the remaining 38% do show some customer-supplier relationships, only 3.8% of suppliers in the acquirer's industry come from the target's industry.

magnitudes of *IIS* are similar for both subsamples, their statistical significance is below conventional levels when the merging entities are from different industries.

In Panel B of Appendix Table A1, we interact *IIS* with the same supply chain risk measures as in Panel A of Table 3. Notably, as shown in the last two columns, the interaction of *IIS* and supply chain risk for public targets is now significant for both subsamples. The interactions are insignificant when we consider all deals, consistent with Table 3, Panel A.

3.4 Other drivers of Import Related Mergers (*IRM*s)

While our results show that supply chain uncertainty and the need to identify suppliers of a firm's core imported inputs could be a powerful driver of *IRM*s, we next show that *IRM*s also occur as firms expand their international operations and require new inputs. In our sample, we have 553 deals with *IIS* larger than zero, and 584 deals with *IIS* equal to 0. Since the coefficient of standalone supply chain risk is insignificant for the likelihood of a merger in Table 3, it appears that supply chain risk is not a primary motivating factor for deals with *IIS*=0.[16]

For these *IIS*=0 deals, we argue that the motive is not to seek supply-chain resilience for existing inputs, but rather expansion into new ones. An acquirer may seek to source new inputs internationally to support new product lines, enter new markets, or lower costs by shifting away from domestic suppliers. Acquiring a target with an established network for these new inputs

[16] In addition, we construct an input similarity score based on the import profiles of all the firms in the acquirer's industry and that of the target. Such a similarity score could represent inputs that the acquirer could potentially want to import from the target's suppliers (e.g., these could represent inputs that the acquirer currently obtains from domestic sources, or are needed for product varieties or technologies that rivals some have adopted). However, for deals with *IIS*=0, while this similarity score is marginally significant in predicting the likelihood of a merger, its interaction with supply chain risk is insignificant. This suggests that rather than enhancing supply chain resilience, these acquirers intend to source new inputs internationally, and seek to overcome the search and contracting frictions of forming new supplier relationships through these acquisitions. These results are reported in Online Appendix OA1.

allows the firm to overcome the significant search and contracting frictions associated with building international supplier relationships from scratch.

This expansionary motive is consistent with the framework of Bernard et al. (2018), who demonstrate that a firm's decisions across various margins of international trade—such as exporting and importing—are highly interdependent and complementary. Their model posits that expansion along one margin reinforces the incentive to expand along others. For example, incurring the fixed cost to serve a new export market increases a firm's revenue and scale. This larger scale makes it more profitable to incur the fixed costs of sourcing inputs from new countries, which in turn lowers production costs and further enhances the profitability of exporting.

[Insert Table 4 Here]

Our findings align with this theory of co-movement. In Table 4, we show that for both the subgroups with *IIS*>0 and *IIS*=0, an acquirer's expansion on the export side—measured by the previous period's trading volume to non-U.S. countries, the number of destination countries the firm exports to, and the number of products exported—strongly predicts the likelihood of an *IRM*. This pattern remains robust, regardless of whether we use measures capturing acquirers' exporting activities in the year of mergers or the year preceding mergers. These variables of exporting activities act as proxies for the expansionary pressures that drive firms to become more globally engaged. As firms grow their export footprint, the need for a more robust and extensive supply chain becomes critical. This includes both ensuring reliability for core inputs (a resilience motive, stronger for *IIS*>0 deals) and identifying suppliers for new inputs required for new products or markets (an expansion motive, relevant for all *IRM*s and especially for *IIS*=0 deals). Our evidence suggests that Import Related Mergers (*IRM*s) serve as a key strategic channel through which firms meet these intensified supply chain demands spurred by their global growth.

3.5. Information Channels: How Do Acquirers Identify Targets in IRMs?

Identifying suitable targets that possess the requisite international supply chain resources is a critical, yet challenging, task for firms seeking to mitigate international supply-chain risks and disruptions through *IRM*s. This challenge arises from significant information asymmetries. In the United States, although publicly listed firms must disclose major customers accounting for over 10% of their total sales, they face no such requirement for suppliers. Moreover, private firms are seldom obligated to disclose any supply-chain relationships. Even when some public firms voluntarily mention international suppliers in contractual disclosures, such information is typically selective and discretionary. Consequently, the probability of accurately mapping a potential target's international supply chain network through public disclosures alone is small.

We posit that acquirers likely circumvent this informational barrier through two channels. The first is the recruitment of former employees from the potential targets. These individuals possess private and strategic knowledge of the a potential target's international supply chain partners and the nature of the products traded. The second channel involves the utilization of third-party proprietary data, such as the S&P *Panjiva* dataset we employed in this study. However, this approach requires the acquirer to possess the analytical capability to track and analyze complex data. In this section, we test the efficacy of these two information acquisition channels. We conjecture that the likelihood of an *IRM* is higher when an acquirer has either recruited former employees from the target or employs data analysts capable of leveraging proprietary data.

[Insert Table 5 Here]

We examine the first channel in Table 5, where the key independent variable, *HasSCMove* is an indicator variable equal to one if, in the three years preceding the deal announcement, the acquirer (placebo acquirer) hired at least one former employee of the target (placebo target) who previously worked in a supply-chain–related role at the placebo target firm, and zero otherwise. We identify supply-chain–related employees based on their job role or title. Specifically, employees are classified as supply-chain–related if their position corresponds to typical supply chain functions—for example, purchasing managers, purchasing agents, buyers, supply chain managers, logisticians, logistics managers, procurement clerks, production planners and expeditors, cargo and freight agents, customs brokers, or compliance officers involved in import/export or trade operations. Additionally, employees are classified as supply-chain–related if their job title contains terms such as “supply chain”, “import”, “supplier”, “procure”, or “purchasing”. This variable is constructed using career history data from the Revelio Labs database. Following the approach in Panel B of Table 4, we partition the sample based on whether Imported Input Similarity (*IIS*) is positive or zero. Our primary focus is whether *HasSCMove* predicts the actual deal, and whether the coefficients for *HasSCMove* is different for the two subgroups, which captures the interaction effect between *IIS* and recruitment of supply-chain experts from the target on the probability of forming an *IRM*.

Columns (1) and (2) present results for the full sample, which includes both public and private targets. Consistent with Cen, Harford, and Xie (2025), we find a positive unconditional effect of recruiting from the target on merger likelihood in both subgroups. This effect is substantially stronger for the subgroup with positive *IIS*. The difference in the *HasSCMove* coefficients between the two groups is 0.077, significant at the 10% level. When we restrict the analysis to public targets in columns (3) and (4), this difference becomes both economically larger and statistically more significant.

[Insert Table 6 Here]

Table 6 examines the second information acquisition channel: the employment of data analysts. Consistent with Cen, Han, Han, and Jo (2025), we define data analysts as data scientists specializing in business intelligence and analytics, based on job descriptions in the Revelio Labs database. The empirical specification mirrors that of Table 5. Our key independent variable, *Log(1+Num DA)*, is the natural logarithm of one plus the number of data analysts employed by the acquirer (placebo acquirer) at the end of the year preceding the deal announcement.

The results in columns (1) and (2) of Table 6, which use the full sample, indicate that employing data analysts increases the probability of a merger only when imported input similarity (*IIS*) is positive. The difference in the coefficients for *Log(1+Num DA)* is 0.012 and is statistically significant at the 10% level. This effect is both economically and statistically stronger in the subsample of public targets, as shown in columns (3) and (4). This pattern, observed in both Tables 5 and 6, is likely driven by the superior coverage and data quality for employees of publicly listed firms in the Revelio Labs database, from which both *HasSCMove* and *Log(1+Num DA)* are constructed.

In summary, the findings in this section demonstrate that firms are more likely to strategically acquire domestic targets possessing international value networks that can mitigate international supply-chain risk, particularly when they enjoy information channels that can reduce the cost of identifying international supply chain networks of potential targets.

3.6. Economic Outcomes after Deals

We now proceed to examine the economic impact of the deals, focusing on how the input sourcing of the acquirers changes following deal completion. To conduct these tests, we impose the condition that all identified units (consignees) of the target firm prior to the deal continue to be identified as a consignee after the deal. This makes it less likely that changes in the acquirer's — that is, that of all consignees that are identified as being associated with the acquirer prior to the deal—importing behavior from target suppliers reflect integration of the target's operations with that of the acquirer. Figure 1 explains this research setup. We define this subset of transactions as the "restricted sample" in our analysis, and refer to the pre-deal acquirer units collectively as "acquirer" in our subsequent discussion of the results.

3.6.1. New International Supplier Relationships

We begin by retaining all actual and placebo acquirers from the restricted sample to examine whether actual acquirers add new international suppliers and source from a larger set of countries following acquisition, compared to placebo acquirers. We continue to use the same set of acquirer firm characteristics as control variables in this test. To ensure comparability, we maintain the cohort fixed effects, thereby limiting our comparisons to within-cohort differences between actual and placebo acquirers.

The results of these analyses are presented in Panels A and B of Table 7. In the first column of Panel A, the dependent variable is the average number of new suppliers in the three-year period following the deal that the acquirer imports from that had no prior history of exporting to the acquirer. In the second column, it is the average number of new countries that the acquirer imports from.

[Insert Table 7 Here]

The results presented in Panel A of Table 7 indicate that compared to the acquirers in the placebo deals, those in the actual deals add significantly more new suppliers and new source countries for their imports. In Panel B of Table 7, we examine separately the subsamples for *IIS>0* and *IIS=0* actual deals. We find that acquirers in both types of deals add more new suppliers and new source countries following the deals. The subsample of acquirers with positive *IIS* with the target adds significantly more new suppliers, which is expected if these deals are primarily motivated by the need to improve the reliance of the supply chains by locating alternative suppliers for the required inputs. However, the number of new sourcing countries is not significantly different for the two groups.

*IRM*s are attractive not only because they enable an acquirer to gain access to the target's relationships with key suppliers, but also because they make it possible to do so *quickly*, relative to incurring the time-costs of establishing new relationships. To show this, we again appeal to the logic of Bernard et al. (2018)—that exporting to new markets increases a firm's production scale, which in turn makes it worthwhile to pay the fixed costs associated with establishing new international supply chains for its inputs. This creates a powerful, self-reinforcing loop where exporting facilitates importing (and as the paper also notes, the resulting lower costs from importing can then facilitate further exporting). By treating the volume of exports (alternatively, number of products exported, or foreign sales) as shocks that make it profitable to add new international suppliers of (possibly new) imported products, we examine whether IRMs enable firms to add more international suppliers in the following period. Consistent with our prediction, the results in Appendix Table A2 show a positive and significant interaction effect between *True* and our proxies for import expansion incentives on the number of new suppliers added in the three-year post-deal period.

Finally, as a robustness check, rather than base our counterfactuals on the placebo deals, we identify a sample of withdrawn *IRM* deals, following Bena and Li (2014). These deals are then matched with a sample of completed deals. We are able to identify 44 withdrawn *IRM*s, and completed deals are matched based on the acquirer-target pair belonging to the same 2-digit SIC industries, the completed deal occurring within a five-year window of the withdrawn deal centered on the announcement year of the corresponding withdrawn, and the acquirer in the completed deal being closest in size to the acquirer in the cancelled deal. We end up with a sample of 77 deals because some withdrawn deals share the same matched deal. In Table A3 of the Appendix, we show that acquirers in completed deals add more new suppliers post-deal, and this effect is stronger for those completed deals with higher *IIS*.

Overall, these results support our initial hypothesis that *IRM*s result in changes to an acquiring firm's existing international supplier network. This effect is stronger for acquirers with greater overlap of imported inputs with the target, suggesting a motive for reducing dependence on existing suppliers of imported inputs. However, even acquirers with no overlap enter into new supplier relationships. We next provide evidence that, for both types of acquirers, taking advantage of the target's supplier relationships and circumventing the frictions of establishing relationships from scratch are key motives for these deals.

3.6.2. Changes in the Importing Behavior of Acquirers After *IRM*s

In this section, we provide granular evidence that the *IRMs* indeed result in the acquirers changing their sourcing from international suppliers. Specifically, we examine whether, after deal completion, acquirers start importing from target suppliers both inputs they had already been importing ("existing" inputs) from other international suppliers, as well as ones they did not import before but were imported by some firms in the rest of the industry ("new" inputs).[17] We are

[17] The last requirement implies that the input is relevant for the acquirer's industry. Our results do not depend on this requirement.

especially interested in testing whether the acquirer imports more from a target supplier when the latter has a longer relationship with the target. We also examine whether this sourcing pattern is more intense for deals in which the acquirer and target have a greater overlap of imported inputs prior to the deal (higher *IIS*).

We organize our "restricted sample" for a period from three years before to three years after deal completion at the acquirer-target supplier-year level. We carry out stacked difference-in-difference regressions in this sample as outlined in Equation (2) below:

$$Buy_{i,s,t} = Post_{i,s,t} \times True_{i,s,t} + Post_{i,s,t} + True_{i,s,t} + Acquirer\ Controls_{i,t} + Target's\ Supplier \times Acquirer\ FE + Deal - Year\ FE \quad (2)$$

where *i* denote the acquirer, *s* the international supplier of the target *j*, and *t* the year. The dependent variable, *Buy*, is a binary indicator that equals one if acquirer *i* imports from target *j*'s supplier *s* in year *t*. We also examine two variations of *Buy*: *BuyExisting*, a dummy variable that equals one if acquirer *i* imports from supplier *s* in year *t* and the imported products consist of input goods previously sourced by the acquirer from other international suppliers before the deal, and *BuyNew*, a dummy variable that equals one if acquirer *i* imports from suppliers in year *t* and the imported products include input goods not previously procured by the acquirer prior to the deal, but imported by the acquirer's peers in its SIC3 industry. *Post* is a dummy variable indicating the post-deal period, taking the value of one for years following deal completion. Similar to previous tests, *True* is a binary indicator equal to one for actual deals and zero for placebo deals. Our empirical specification includes acquirer-supplier pair fixed effects to control for time-invariant determinants at the acquirer-supplier level and cohort-year fixed effects to control for market-wide shocks affecting all firms around deal completion. The key variable of interest is the interaction term *Post*×*True*, whose coefficient captures the differential change in importing behavior between actual and placebo acquirers following deal completion. Results are presented in Panel A of Table 8.

[Insert Table 8 Here]

The findings presented in Panel A of Table 8 indicate that acquirers exhibit a significantly higher increase in the probability of importing from their targets' international suppliers following deal completion compared to placebo acquirers in placebo deals. Specifically, the differential increase in import probability for actual acquirers relative to the control group from a target supplier is 4.2 percentage points. Given that acquirers' pre-deal import probability from targets' international suppliers stood at 1.7%, this difference in the change of the likelihood of importing from targets' international suppliers can be translated to 247.1% of the pre-deal level. This pattern is robust across all specifications in Panel A of Table 8, including analyses restricted to both previously imported product categories and new imported input introductions of acquirers.

Our results in Panel A of Table 8 suggest that inheriting the target's supplier relationships is likely to be a major motive for the IRMs. These relationships are intangible assets that enable the acquirers to find alternative suppliers without having to incur the search costs and contracting frictions that would otherwise be required if relationships had to be built from scratch. This logic also implies that the most attractive of those relationships are the ones that have survived the longest. To test this prediction, we partition the sample used in Panel A into two subgroups based on the duration of supply-chain relationships between the target firm and its international supplier. The *long-relationship* group comprises observations where the target-supplier relationship has lasted at least three years (the sample mean rounded to the nearest whole number), while the remaining observations are classified into the *short-relationship* group. We then estimate the same regression model specified in Equation (2) separately for these subgroups and test for differences in the coefficients of *Post×True* between the two groups. The results are presented in Panel B of Table 8.

Consistent with our conjecture, the pattern documented in Panel A is significantly more pronounced in the *long-relationship* group. In columns (1) and (2) of Panel B, where *Buy* serves as the dependent variable, the coefficient on *Post×True* is 0.077 for the *long-relationship* group compared to 0.030 for the *short-relationship* group. This difference, statistically significant at the 1% level (equivalent to a triple interaction estimate), implies that the difference-in-differences effect in the *long-relationship* group is more than double that of the *short-relationship* group. A similar pattern emerges in columns (3)-(6) of Panel B, where we replicate the analysis using *BuyNew* and *BuyExisting* as dependent variables. These findings underscore the importance of the target's prior experience with international suppliers, supporting our argument that long-term relationships mitigate hold-up problems and reduce due diligence costs, thereby enhancing the deal's attractiveness to acquirers.

We check the robustness of these results for the sample of matched completed and withdrawn deals introduced in Section 3.4.1. We find consistent results. As reported in Appendix Table A4, the coefficient of the interaction term *Post×True* is positive and significant when the dependent variable is *Buy*, *BuyNew*, and *BuyExisting* at the 5% level of significance or higher, with magnitude comparable to those in Panel A of Table 8.

Next, in Panel C of Table 8, we partition our restricted sample based on whether the actual deal has positive or zero *IIS*. While the coefficient of *Post×True* is positive and significant (at the 1% level) for both subgroups with *Buy*, *BuyNew*, and *BuyExisting* as the dependent variable, it is twice as large for the *IIS>0* group than for the *IIS=0* group. This supports our argument that more imported input overlap affords an opportunity to achieve more supply chain resilience via an *IRM*, and is consistent with our earlier result that the merger likelihood is higher for higher *IIS* deals.[18]

How does the importing behavior of the acquire from its *existing* suppliers change after the deal? If the mergers are indeed motivated by the need to bolster the resilience of the supply chain, we would expect a reduced reliance on acquirers' existing international suppliers post-merger. This is exactly what we find. In Appendix Table A5, we show that the acquirer is less likely to continue with an existing supplier after the deal, and this effect is stronger the greater is *IIS*.

3.6.3 Retaining Targets' Supply-Chain Talents after *IRM*s

The economics of Relational Contract Theory discussed in the Introduction suggests that the target's relationships, especially the long-standing ones, are valuable to any potential buyer that would like to import the inputs that these suppliers can provide. Key to the continuity of these relationships are the target employees who specialize in supply-chain management. Accordingly, contrary to the usual tendency of target employees facing higher likelihood of layoffs following mergers, for *IRM*s, we expect these supply-chain experts to be retained. A test of this hypothesis is, therefore, a "smoking gun" that would validate our core hypothesis.

We test this hypothesis by analyzing employee-level data on target employee retention. Our empirical test utilizes a sample comprising both actual and placebo deals, where actual acquirers are paired with actual and placebo targets. The unit of observation is at the acquirer-target-target's employee level, encompassing all employees of the target firm (actual and placebo) prior to the deal announcement. The dependent variable, *Leave3y,* is a binary indicator equal to

[18] In an untabulated result, we also find that the target units are more likely to buy from the acquirer's suppliers; however, the economic magnitudes of these effects are small.

one if the employee leaves the target firm within three years of the announcement and does not transition to any unit of the acquirer. An analogous variable, *Leave5y*, measures departures over a five-year horizon.

The key independent variables are defined as follows. *SC_Role* is an indicator variable that equals one if the employee's job nature or job title is supply-chain related. Specifically, supply-chain related positions include roles such as purchasing managers, purchasing agents, buyers, supply chain managers, logisticians, logistics managers, procurement clerks, production planners and expediters, cargo and freight agents, customs brokers, and compliance officers involved in import/export or trade operations. Supply-chain-related job titles include those containing the terms "supply chain," "import," "supplier," "procure," or "purchasing". Similar to earlier tests, the variable, *True,* is a dummy distinguishing actual deals (1) from placebo deals (0), and *Positive IIS* is a dummy variable indicating a positive import incentive score (IIS) between the acquirer and target. The variable of primary interest is the triple interaction term, *SC_Role*×*True*×*Positive IIS*. A negative and statistically significant coefficient on this term would indicate that supply-chain talent is more likely to be retained following actual *IRM*s—where international supply-chain integration is a key motive—compared to other deals. The results of this analysis are presented in Table 9.

[Insert Table 9 Here]

In column (1), we employ *Leave3y* as the dependent variable and restrict the sample to target employees with more than three years of tenure at the time of the deal announcement. This subsample is likely to comprise individuals who have made significant relationship-specific human capital investments with international suppliers. The results for this group reveal several key patterns. First, the coefficient on *True* is positive and statistically significant, which aligns with the well-established finding that employees of actual targets experience higher turnover (e.g., layoffs in post-deal integration) than those in placebo deals. Second, the positive and significant coefficient on *SC_Role* indicates that supply-chain talent exhibits greater inherent mobility in the labor market, irrespective of corporate merger activity. Third, the negative and significant coefficient on the interaction term *True×Positive IIS* suggests that acquirers in *IRM*s are generally more likely to retain all long-tenured employees from the target firm compared to other deals. Most critically, the coefficient on the triple interaction term, *SC_Role×True×Positive IIS*, is also negative and statistically significant. This indicates an incremental retention likelihood for long-tenured target employees who possess supply-chain expertise in *IRM*s.

In column (2), we replicate the analysis on the subsample of employees with less than three years of tenure. The most notable distinction from the results in column (1) is the coefficient on the triple interaction term: its economic magnitude is approximately halved and it is no longer statistically significant. This finding supports our conjecture that building trust and effective relationships with international supply-chain partners requires long-term and relationship-specific human capital investments. To assess the robustness of our findings across different time horizons, we repeat the tests using *Leave5y* as the dependent variable in columns (3) and (4) for the long-tenure and short-tenure subsamples, respectively. The patterns observed are qualitatively similar to those in the first two columns, reinforcing the conclusion that the labor market impact of *IRM*s, particularly the retention of key supply-chain human capital, is consistent across different measurement periods.

4. Another Possible Supply-Chain-Driven Motive: Vertical Foreclosure

4.1 Target Competitors' Pre-Deal Purchase from Acquirer's International Suppliers and M&A Likelihood

In Section 3, we presented evidence that, given the frictions associated with establishing new supplier relationships in the Global Value Chain, a U.S. domestic firm may find it attractive to acquire a target that sources inputs that the potential acquirer needs for its production processes. The vetting process associated with merger due diligence is likely to identify the more productive relationships, and even when control passes to the acquirer, it is in neither the acquirer nor the supplier's interest to break the relationship.

In this section, we present evidence of a different supply-chain-driven motive for *IRM*s, related to vertical foreclosure. We argue that the same frictions discussed above of starting new relationships from scratch place the target's competitors at a disadvantage when their supply chains overlap with the acquirer's. Specifically, we argue that an acquirer can leverage its influence over existing international suppliers by restricting their collaboration with the target firm's competitors, especially when it has a longer relationship with these suppliers relative to the target's rivals. If the acquisition price primarily reflects the pre-deal competitive dynamics of the target industry, the acquirer can enhance the target's value by foreclosing the access of the target's competitors to its key suppliers. This generates operational synergies by reducing competition in the product market.

To examine whether this economic incentive also drives mergers and acquisitions, we augment the test specification outlined in Equation (1) by measures capturing the purchases of the target's competitors from the acquirer's international suppliers before the deal. We use two alternative measures to capture different dimensions of the purchase of target's competitors: *RivalPurchaseVol* is the aggregated volume of goods purchased by target's competitors from the acquirer's suppliers in the year prior to the deal announcement year; and *RivalPurchaseNum* is the number of target's competitors that import from the acquirer's suppliers in the year prior to the deal announcement year. We still keep the imported input similarity and product similarity as control variables. Similar to the test specification outlined in Equation (1), we include the cohort fixed effects in all test specifications. Standard errors are clustered at the cohort level.

[Insert Table 10 Here]

The results reported in Table 10 support our conjecture. Both the volume and the number of purchases made by target competitors from the acquirer's international suppliers exhibit a positive and statistically significant association with the likelihood of mergers and acquisitions. This finding remains robust across specifications, regardless of whether we control for acquirer firm characteristics. The estimated effects are economically meaningful as well as statistically significant. For instance, in column (1) of Panel A, the coefficient on *RivalPurchaseVol* (0.136), significant at the 1% level, implies that a one-standard-deviation increase in *RivalPurchaseVol* corresponds to an increase in M&A likelihood by 2.6 percentage points, equivalent to 22.8% of the mean M&A probability in our sample.

In Panel B of Table 10, we further investigate whether this effect is amplified when the acquirer possesses greater influence over its international suppliers. We proxy the strength of this influence using *HighExp*, a binary variable equal to one if the acquirer has maintained relationships with its international suppliers for three or more years. By interacting *HighExp* with our two measures of *TarRivalPurchase*, we find that the coefficients on the interaction terms are positive and statistically significant. This confirms our prediction that the positive relationship between M&A likelihood and pre-deal competitor purchases from the acquirer's international suppliers is more pronounced when the acquirer has greater influence over its suppliers.

4.2. Post-Deal Changes in Target Competitors' Imports from Acquirers' International Suppliers

The acquirer's influence over the international supply chains of the target's rivals is likely to generate competitive benefits for the targets even in the absence of actual foreclosure, since the mere threat or capability of disrupting the rival's supply chains is likely to generate these benefits. Nonetheless, we next investigate whether the competitors of a target reduce their imports from the acquirers' international suppliers after deal completion, that is, there is some degree of foreclosure. To do so, we aggregate the number of targets' product market competitors at the acquirer-target-year level. We exclude the observations where the target's competitors have not imported from any of the acquirer's international suppliers prior to the deal (since, for this sample, their imports from the acquirer's international suppliers will never decrease after deal completion, which may lead to biased estimates). The test specification is outlined in Equation (3) below:

$$NImport_{i,j,t} = Post_{i,j,t} \times True_{i,j,t} + Post_{i,j,t} + True_{i,j,t} + Acquirer\ Controls_{i,t} + Acquirer * Target\ FE + Deal\ Cohort * Year\ FE \quad (3)$$

where *i* denotes the acquirer, *j* the target, and *t* the deal announcement year. The dependent variable, *NImport*, measures the aggregated number of target competitors that import from the acquirer's international suppliers in year *t*. *Post* is a binary indicator equal to one for years following the deal announcement, and *True* is a dummy variable equal to one for actual deals and zero for placebo deals. Since *NImport* captures competitive dynamics in the product market, we include additional control variables. *Log(NSup)* represents the natural logarithm of the number of the acquirer's overseas suppliers; *Log(NRival)* is the natural logarithm of the number of the target's product-market rivals, as defined by the TNIC-3 industry classification; and *Log(Volume to Acq)* denotes the natural logarithm of the acquirer's total import volume. We retain all previously defined acquirer-level firm characteristics as controls. To account for time-invariant determinants of import decisions at the relationship level, we include acquirer-target-pair fixed effects in all test specifications. Results are reported in Table 11.

[Insert Table 11 Here]

The Ordinary Least Squares (OLS) regression results reported in columns (1) and (2) in Table 8 indicate that, relative to that of placebo acquirers, the number of the target's competitors purchasing from the actual acquirer's international suppliers declines more sharply. This difference-in-differences effect is captured by the coefficients of the interaction term *Post×True*, which are statistically significant at the 1% level across both the [t−3, t+3] and [t−5, t+5] windows. Additionally, the results remain robust to nonlinear models (e.g., Poisson regression), which account for the count-based nature of the dependent variable, *NImport*. However, the Poisson regressions are reported without fixed effects as the regressions did not converge when fixed effects are included.

4.3. Vertical Foreclosure and Operating Performance of Target Firms

We next analyse whether targets benefit from the foreclosure effects, i.e., when acquirers exert their influence over the supply chains of the target's competitors, do the targets' operational performance and market values improve after deal completion?

For this test, we retain only publicly traded target firms observed both before and after deal completion, that is, our sample is restricted to targets that remain as standalone entities (i.e., not fully absorbed by their acquirers) that disclose independent financial statements. The analysis still follows a difference-in-differences framework with two event windows: [t–3, t+3] and [t–5, t+5]. The dependent variables measure the operating performance of target firms, including *Tobin's Q*, the natural logarithm of total sales (*LogSale*), return on assets (*ROA*), and profit margin. The key independent variable is the interaction term between *RivalPurchaseVol* and *Post*. All specifications include target firm fixed effects and year fixed effects to account for unobserved heterogeneity.

[Insert Table 12 Here]

The results in Table 12 indicate that target firms experience significant improvements in Tobin's Q and total sales following deal completion. These gains are more pronounced for targets whose competitors source more extensively from the acquirers' international suppliers. However, we find no corresponding improvements in return on assets (ROA) or profit margin, suggesting that the benefits primarily stem from enhanced scale (quantity effects) rather than pricing power in product market competition. Consistent with prior tests, these patterns remain robust across both event windows. Overall, the evidence based on the change of targets' operation performance around deal completion is consistent with our conjecture that targets are able to gain from the foreclosure channel.

5. Conclusion

This paper recasts a significant portion of domestic M&A activity as a strategic acquisition of "relational capital"—the valuable, intangible assets embedded in a target firm's long-standing international supplier relationships. In a global economy characterized by high search costs and contractual frictions, building reliable supply chains from scratch is a formidable challenge. We provide robust evidence that firms circumvent these hurdles by acquiring domestic targets to inherit their vetted supplier networks. Our analysis, using granular transaction-level shipment data, reveals the key signatures of this strategy. We show that post-merger, acquirers systematically begin purchasing from the target's suppliers, with a particularly strong tendency to adopt relationships that are long-established. This behavior supports two distinct motives: acquiring alternative suppliers for existing inputs to enhance resilience, and accessing networks for new inputs to facilitate expansion. The resilience motive is further corroborated by our finding that merger likelihood increases with the similarity of the firms' imported input portfolios, an effect that intensifies during periods of heightened supply-chain risk. Beyond these direct synergies, we uncover a competitive dimension: these mergers also create foreclosure-like effects, disadvantaging the target's rivals and leading to improved sales growth and market valuation for the target firm.

Our findings have important implications for both theory and practice. Theoretically, we expand the scope of M&A motivations beyond traditional horizontal, vertical, or diversifying mergers, introducing supply chain resilience as a distinct driver of corporate transactions. Practically, our results underscore how firms can leverage M&A to navigate an era of heightened geopolitical and supply chain uncertainty, though this may come at the cost of reduced competition. Policymakers should take note of these exclusionary effects, as *IRMs* may warrant scrutiny under antitrust frameworks traditionally focused on vertical or horizontal integration. Future research could explore whether similar patterns emerge in purely domestic supply chains or in other institutional contexts, further illuminating the interplay between corporate strategy and supply chain dynamics.

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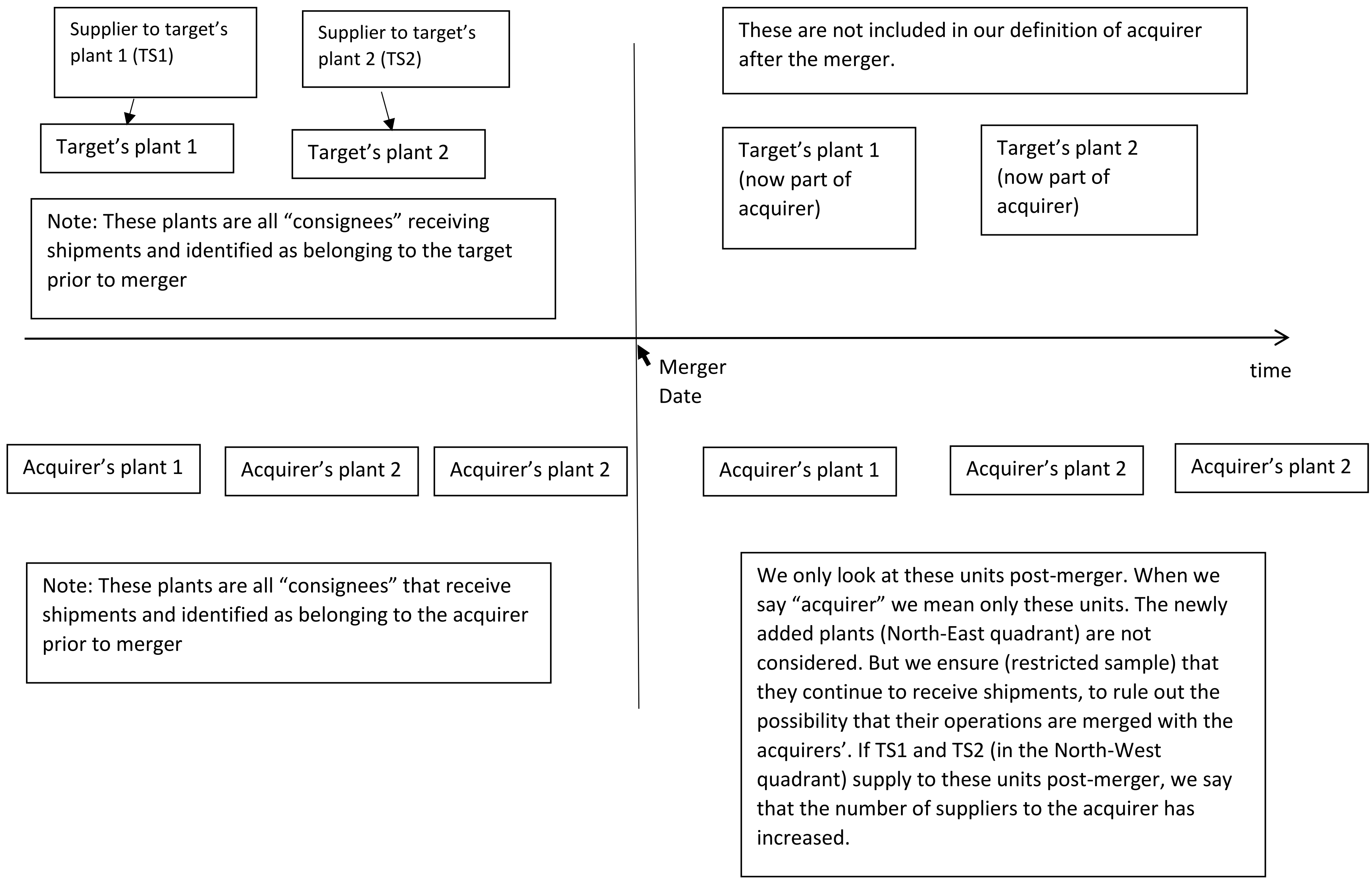

Figure 1: The Setup of the "Restricted Sample"

Table 1. Summary Statistics

This table presents the summary statistics of the regression sample (actual and placebo deals). Our sample covers the period from 2007 to 2020. We exclude mergers in finance (SIC 6000-6999) industries. Variable definitions are provided in Appendix I.

VarName	Obs	Mean	SD	P25	Median	P75
Imported Input Similarity	10035	0.034	0.124	0.000	0.000	0.003
Supplier Similarity	10035	0.002	0.033	0.000	0.000	0.000
Product Similarity	3193	0.014	0.043	0.000	0.000	0.000
RivalPurchaseVol	10035	0.031	0.190	0.000	0.000	0.000
NumRivalPurchase	10035	3.069	24.029	0.000	0.000	0.000
Acquirer LogAsset	10035	7.479	1.990	6.130	7.550	8.759
Acquirer Leverage	10035	0.530	0.230	0.377	0.526	0.665
Acquirer Capex	10035	0.038	0.036	0.015	0.027	0.048
Acquirer Cash	10035	0.118	0.113	0.036	0.086	0.166
Acquirer Dividend	10035	0.018	0.032	0.000	0.002	0.023
Acquirer TobinQ	10035	1.913	1.046	1.235	1.621	2.271
Acquirer ROA	10035	0.031	0.111	0.010	0.049	0.085

Table 2. Imported Input Similarity and Merger Likelihood

This table presents the coefficient estimates from the regressions that examine how imported input similarity affects merger likelihood. The sample is organized at the deal level (acquirer-target-announcement year level), which includes both actual and placebo deals. Each actual acquirer is paired with five placebo targets from the same SIC3 industry, selected based on the closest volume of imports to the actual target. Similarly, each actual target is matched with five placebo acquirers. The dependent variable, *True*, is a dummy variable that equals one for actual deals and zero for placebo deals. In Panel A, *Imported Input Similarity (IIS)* is the cosine similarity of the input products between the acquirer and the target. In Panel B, we utilize the Hoberg-Phillips TNIC3 industry classification to construct Industry Imported Input Similarity (Industry IIS), which represents the average similarity between the target's import vector and that of the peer firms of the acquirer in its TNIC3 industry in the year preceding the merger. In Panel C, we create a new imported similarity score, China Imported Input Similarity (*China IIS*), which is the cosine similarity of the acquirer's inputs imported from China and those of the target that are *not imported* from China. In this panel, *Post* is a dummy variable equal to 1 if the deal announcement is made in years after 2020 (i.e., after the COVID-19 pandemic outbreak). In all panels, *Supplier Similarity* is the cosine similarity of the overseas supplier base between the acquirer and the target. *Product Similarity* is Hoberg-Phillips TNIC3 product similarity score. Deal-cohort fixed effects are included in all test specifications. Definitions of other independent variables are provided in Appendix I. Robust standard errors, clustered at the cohort level, are reported in parentheses. ***, **, and * indicate the 1%, 5%, and 10% levels of statistical significance, respectively.

Panel A. IIS based on product categories

	(1)	(2)	(3)	(4)	(5)
	Public&Private Target	Public&Private Target	Public Target	Public Target	Public Target
VARIABLES	True	True	True	True	True
IIS	0.277***	0.255***	0.166***	0.140**	0.162***
	(0.039)	(0.039)	(0.056)	(0.057)	(0.059)
Supplier Similarity	0.628***	0.633***	0.503***	0.156	
	(0.186)	(0.183)	(0.192)	(0.246)	
Product Similarity				2.046***	2.098***
				(0.310)	(0.308)
Acquirer LogAsset		0.025***	0.032***	0.031***	0.031***
		(0.002)	(0.003)	(0.003)	(0.003)
Acquirer Leverage		-0.020	0.024	0.029	0.029
		(0.014)	(0.025)	(0.024)	(0.024)
Acquirer Capex		-0.419***	-0.255*	-0.273**	-0.270*
		(0.080)	(0.137)	(0.138)	(0.138)
Acquirer Cash		-0.039	-0.001	-0.019	-0.019
		(0.028)	(0.053)	(0.053)	(0.054)
Acquirer Dividend		-0.016	0.074	0.039	0.038
		(0.112)	(0.153)	(0.162)	(0.160)
Acquirer TobinQ		0.006**	0.004	0.003	0.003
		(0.003)	(0.005)	(0.005)	(0.005)
Acquirer ROA		0.126***	0.071*	0.081**	0.081**
		(0.022)	(0.037)	(0.037)	(0.037)
Cohort FE	Yes	Yes	Yes	Yes	Yes
SE Clustered (Cohort)	Yes	Yes	Yes	Yes	Yes
Observations	10,017	10,017	3,183	3,183	3,183
R-squared	0.034	0.054	0.111	0.069	0.111

Panel B. Industry IIS

VARIABLES	(1) Public&Private Target True	(2) Public&Private Target True	(3) Public Target True	(4) Public Target True	(5) Public Target True
IIS	0.239***	0.218***	0.143**	0.121**	0.145**
	(0.042)	(0.042)	(0.058)	(0.059)	(0.061)
Supplier Similarity	0.649***	0.654***	0.519***	0.171	
	(0.183)	(0.180)	(0.191)	(0.246)	
Industry IIS	0.390***	0.380***	0.300*	0.264*	0.250
	(0.108)	(0.106)	(0.153)	(0.152)	(0.152)
Product Similarity				2.040***	2.097***
				(0.309)	(0.306)
Acquirer LogAsset		0.025***	0.032***	0.031***	0.031***
		(0.002)	(0.003)	(0.003)	(0.003)
Acquirer Leverage		-0.021	0.025	0.029	0.030
		(0.014)	(0.025)	(0.024)	(0.024)
Acquirer Capex		-0.425***	-0.260*	-0.278**	-0.275**
		(0.080)	(0.136)	(0.138)	(0.138)
Acquirer Cash		-0.041	-0.001	-0.020	-0.020
		(0.027)	(0.053)	(0.053)	(0.053)
Acquirer Dividend		-0.010	0.080	0.044	0.043
		(0.112)	(0.152)	(0.162)	(0.159)
Acquirer TobinQ		0.006**	0.004	0.003	0.003
		(0.003)	(0.005)	(0.005)	(0.005)
Acquirer ROA		0.127***	0.074**	0.084**	0.083**
		(0.022)	(0.037)	(0.037)	(0.037)
Cohort FE	Yes	Yes	Yes	Yes	Yes
SE Clustered (Cohort)	Yes	Yes	Yes	Yes	Yes
Observations	10,017	10,017	3,183	3,183	3,183
R-squared	0.034	0.054	0.111	0.069	0.111

Panel C: China IIS

VARIABLES	(1) Public&Private Target True	(2) Public&Private Target True	(3) Public Target True	(4) Public Target True	(5) Public Target True
China IIS×Post	0.072	0.072	0.652***	0.696***	0.714***
	(0.152)	(0.147)	(0.246)	(0.244)	(0.247)
China IIS	0.224***	0.214***	0.143*	0.144*	0.152*
	(0.054)	(0.053)	(0.083)	(0.077)	(0.078)
Supplier Similarity	0.826***	0.814***	0.630***	0.255	
	(0.170)	(0.168)	(0.178)	(0.233)	
Product Similarity				2.073***	2.176***
				(0.311)	(0.304)
Acquirer LogAsset		0.026***	0.033***	0.031***	0.031***
		(0.002)	(0.003)	(0.003)	(0.003)
Acquirer Leverage		-0.021	0.028	0.032	0.034
		(0.014)	(0.025)	(0.024)	(0.024)
Acquirer Capex		-0.428***	-0.260*	-0.274**	-0.274**
		(0.080)	(0.136)	(0.138)	(0.139)
Acquirer Cash		-0.042	-0.004	-0.023	-0.024
		(0.028)	(0.053)	(0.054)	(0.054)
Acquirer Dividend		-0.035	0.086	0.050	0.050
		(0.111)	(0.151)	(0.161)	(0.156)
Acquirer TobinQ		0.007**	0.005	0.004	0.003
		(0.003)	(0.005)	(0.005)	(0.005)
Acquirer ROA		0.128***	0.074**	0.083**	0.083**
		(0.022)	(0.037)	(0.037)	(0.037)
Cohort FE	Yes	Yes	Yes	Yes	Yes
SE Clustered (Cohort)	Yes	Yes	Yes	Yes	Yes
Observations	10,017	10,017	3,183	3,183	3,183
R-squared	0.028	0.049	0.069	0.112	0.110

Table 3. Imported Input Similarity, Supply Chain Risk, and Merger Likelihood

This table reports the coefficients of regressions that examine whether the role of imported input similarity in determining merger likelihood is strengthened when firms experience higher supply-chain risks. We consider three measures of supply chain risks: Panel A uses acquirer-specific supply chain risks, following Ersahin, Giannetti, and Huang (2024); Panel B uses economy-wide supply chain risks, measured as the average supply chain risk in a given year; and Panel C incorporates trade policy uncertainty, proxied by the Trade Policy Uncertainty Index from Caldara, Iacoviello, Molligo, Prestipino, and Raffo (2020). The test specifications in this table follow those in Table 2, where the dependent variable, *True*, equals one for actual deals and zero for placebo deals. *Imported Input Similarity* (*IIS*) measures the cosine similarity of input products between the acquirer and the target. *IIS* is interacted with each supply chain risk measure. Definitions of other independent variables are provided in Appendix I. Cohort fixed effects are included in all specifications. Robust standard errors, clustered at the cohort level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Acquirer-Specific Supply-Chain Risks

	(1)	(2)	(3)	(4)	(5)
	Public&Private Target	Public&Private Target	Public Target	Public Target	Public Target
VARIABLES	True	True	True	True	True
IIS×SC Risk$_{t-1}$	0.004	0.004	0.009***	0.006**	0.005**
	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)
IIS	0.299***	0.285***	0.183**	0.177**	0.247***
	(0.054)	(0.054)	(0.082)	(0.081)	(0.081)
Supplier Similarity	0.718***	0.721***	0.674***	0.487*	
	(0.176)	(0.171)	(0.187)	(0.267)	
SC Risk$_{t-1}$	0.000	0.000	-0.001	-0.001	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Product Similarity				2.540***	2.613***
				(0.447)	(0.452)
Acquirer LogAsset		0.028***	0.034***	0.031***	0.031***
		(0.003)	(0.004)	(0.005)	(0.005)
Acquirer Leverage		-0.042**	0.058	0.074*	0.075*
		(0.021)	(0.037)	(0.038)	(0.039)
Acquirer Capex		-0.484***	-0.279	-0.378	-0.369
		(0.127)	(0.229)	(0.231)	(0.233)
Acquirer Cash		-0.079*	0.035	0.005	0.010
		(0.041)	(0.084)	(0.085)	(0.087)
Acquirer Dividend		0.139	0.140	0.074	0.059
		(0.164)	(0.220)	(0.229)	(0.231)
Acquirer TobinQ		0.000	-0.006	-0.007	-0.008
		(0.004)	(0.006)	(0.006)	(0.006)
Acquirer ROA		0.124***	0.128*	0.148*	0.152*
		(0.043)	(0.077)	(0.077)	(0.077)
Cohort FE	Yes	Yes	Yes	Yes	Yes
SE Clustered (Cohort)	Yes	Yes	Yes	Yes	Yes
Observations	6,850	6,850	2,156	2,156	2,156
R-squared	0.060	0.073	0.095	0.151	0.146

Panel B: Economy-Wide Supply-Chain Risks

VARIABLES	(1) Public&Private Target True	(2) Public&Private Target True	(3) Public Target True	(4) Public Target True	(5) Public Target True
IIS×EconomySC Risk$_{t-1}$	0.059	0.054	0.282**	0.347***	0.348***
	(0.077)	(0.077)	(0.131)	(0.131)	(0.128)
IIS	0.032	0.030	-0.988*	-1.282**	-1.264**
	(0.322)	(0.320)	(0.531)	(0.535)	(0.521)
Supplier Similarity	0.631***	0.636***	0.506***	0.154	
	(0.183)	(0.180)	(0.179)	(0.228)	
Product Similarity				2.081***	2.132***
				(0.305)	(0.301)
Acquirer LogAsset		0.025***	0.033***	0.031***	0.031***
		(0.002)	(0.003)	(0.003)	(0.003)
Acquirer Leverage		-0.020	0.027	0.033	0.033
		(0.014)	(0.025)	(0.024)	(0.025)
Acquirer Capex		-0.418***	-0.243*	-0.258*	-0.256*
		(0.080)	(0.137)	(0.137)	(0.137)
Acquirer Cash		-0.039	0.002	-0.017	-0.017
		(0.027)	(0.053)	(0.054)	(0.054)
Acquirer Dividend		-0.013	0.093	0.061	0.061
		(0.112)	(0.149)	(0.156)	(0.154)
Acquirer TobinQ		0.006**	0.004	0.003	0.003
		(0.003)	(0.005)	(0.005)	(0.005)
Acquirer ROA		0.127***	0.071*	0.081**	0.081**
		(0.022)	(0.037)	(0.037)	(0.037)
Cohort FE	Yes	Yes	Yes	Yes	Yes
SE Clustered (Cohort)	Yes	Yes	Yes	Yes	Yes
Observations	10,017	10,017	3,183	3,183	3,183
R-squared	0.034	0.054	0.072	0.115	0.115

Panel C: Trade Policy Uncertainty

VARIABLES	(1) Public&Private Target True	(2) Public&Private Target True	(3) Public Target True	(4) Public Target True	(5) Public Target True
IIS×TradePolicyUncertainty$_{t-1}$	0.000	0.000	0.003*	0.003*	0.003**
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Input Similarity	0.256***	0.232***	0.056	0.017	0.034
	(0.058)	(0.057)	(0.085)	(0.085)	(0.087)
Supplier Similarity	0.629***	0.634***	0.494***	0.145	
	(0.185)	(0.182)	(0.191)	(0.246)	
Product Similarity				2.055***	2.104***
				(0.306)	(0.303)
Acquirer LogAsset		0.025***	0.033***	0.031***	0.031***
		(0.002)	(0.003)	(0.003)	(0.003)
Acquirer Leverage		-0.020	0.026	0.031	0.031
		(0.014)	(0.025)	(0.024)	(0.024)
Acquirer Capex		-0.417***	-0.243*	-0.260*	-0.257*
		(0.080)	(0.137)	(0.139)	(0.139)
Acquirer Cash		-0.038	0.002	-0.016	-0.016
		(0.028)	(0.053)	(0.054)	(0.054)
Acquirer Dividend		-0.015	0.077	0.042	0.041
		(0.112)	(0.150)	(0.159)	(0.157)
Acquirer TobinQ		0.006**	0.004	0.003	0.002
		(0.003)	(0.005)	(0.005)	(0.005)
Acquirer ROA		0.126***	0.072*	0.081**	0.081**
		(0.022)	(0.037)	(0.037)	(0.037)
Cohort FE	Yes	Yes	Yes	Yes	Yes
SE Clustered (Cohort)	Yes	Yes	Yes	Yes	Yes
Observations	10,017	10,017	3,183	3,183	3,183
R-squared	0.034	0.054	0.072	0.115	0.115

Table 4. Acquirers' Exporting Activities, Imported Input Similarity, and Merger Likelihood

This table presents the coefficient estimates from the regressions that examine how an acquirer's prior exporting activities affect its likelihood of engaging in mergers and acquisitions. The sample is organized at the deal level (acquirer-target-announcement year level), which includes both actual and placebo deals. Each actual acquirer is paired with five placebo targets from the same SIC3 industry, selected based on the closest volume of imports to the actual target. Similarly, each actual target is matched with five placebo acquirers. The dependent variable, *True*, is a dummy variable that equals one for actual deals and zero for placebo deals. An acquirer's exporting activities are captured by the natural logarithm of one plus its export volume in Panel A, the natural logarithm of one plus the number of countries it exports to in Panel B, and the natural logarithm of one plus the number of products it exports to other countries in Panel C. In columns (1) and (2), we include the acquirer's exporting activity variables at the year of announcement as the key independent variable for subgroups where IIS is equal to zero or larger than zero. Similarly, in columns (3) and (4), we include the lagged variable that captures the acquirer's exporting activities one year before the deal announcement as the key independent variable. Definitions of other independent variables are provided in Appendix I. Cohort fixed effects are included in all specifications. Robust standard errors, clustered at the cohort level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Total Volume of Products A Firm Exports To Other Countries

	(1)	(2)	(3)	(4)
	Public&Private Target	Public&Private Target	Public&Private Target	Public&Private Target
	IIS=0	IIS>0	IIS=0	IIS>0
VARIABLES	True	True	True	True
Log(1+Export Volume)$_t$	0.004*	0.011***		
	(0.002)	(0.003)		
Log(1+Export Volume)$_{t-1}$			0.005**	0.010**
			(0.002)	(0.004)
Industry IIS	0.335*	0.431***	0.330*	0.429***
	(0.173)	(0.125)	(0.173)	(0.125)
Acquirer LogAsset	0.020***	0.025***	0.020***	0.026***
	(0.002)	(0.004)	(0.002)	(0.004)
Acquirer Leverage	-0.032*	-0.026	-0.033**	-0.029
	(0.016)	(0.034)	(0.016)	(0.034)
Acquirer Capex	-0.302***	-0.554**	-0.303***	-0.574***
	(0.090)	(0.217)	(0.091)	(0.217)
Acquirer Cash	-0.020	-0.142*	-0.020	-0.146*
	(0.032)	(0.077)	(0.032)	(0.077)
Acquirer Dividend	0.001	0.127	-0.000	0.118
	(0.137)	(0.246)	(0.137)	(0.246)
Acquirer TobinQ	0.004	-0.000	0.004	-0.001
	(0.003)	(0.006)	(0.003)	(0.006)
Acquirer ROA	0.096***	0.290***	0.096***	0.288***
	(0.027)	(0.058)	(0.027)	(0.058)
Cohort FE	Yes	Yes	Yes	Yes
SE Clustered (Cohort)	Yes	Yes	Yes	Yes
Observations	6,333	3,436	6,333	3,436
R-squared	0.086	0.122	0.086	0.122

Panel B: Number of Countries A Firm Exports Its Products To

VARIABLES	(1) Public&Private Target IIS=0 True	(2) Public&Private Target IIS>0 True	(3) Public&Private Target IIS=0 True	(4) Public&Private Target IIS>0 True
Log(1+Export Country)$_t$	0.016**	0.024**		
	(0.006)	(0.010)		
Log(1+Export Country)$_{t-1}$			0.020***	0.024**
			(0.007)	(0.011)
Industry IIS	0.334*	0.430***	0.327*	0.427***
	(0.173)	(0.125)	(0.173)	(0.125)
Acquirer LogAsset	0.019***	0.025***	0.019***	0.026***
	(0.002)	(0.004)	(0.002)	(0.004)
Acquirer Leverage	-0.031*	-0.026	-0.033**	-0.027
	(0.016)	(0.034)	(0.016)	(0.035)
Acquirer Capex	-0.295***	-0.561**	-0.292***	-0.565***
	(0.090)	(0.217)	(0.091)	(0.218)
Acquirer Cash	-0.021	-0.143*	-0.019	-0.141*
	(0.032)	(0.077)	(0.032)	(0.078)
Acquirer Dividend	-0.004	0.135	-0.006	0.122
	(0.136)	(0.245)	(0.137)	(0.247)
Acquirer TobinQ	0.004	-0.001	0.004	-0.001
	(0.003)	(0.006)	(0.003)	(0.006)
Acquirer ROA	0.096***	0.287***	0.096***	0.285***
	(0.026)	(0.058)	(0.027)	(0.058)
Cohort FE	Yes	Yes	Yes	Yes
SE Clustered (Cohort)	Yes	Yes	Yes	Yes
Observations	6,333	3,436	6,333	3,436
R-squared	0.086	0.122	0.087	0.121

Panel C: Number of Products A Firm Exports to Other Countries

VARIABLES	(1) Public&Private Target IIS=0 True	(2) Public&Private Target IIS>0 True	(3) Public&Private Target IIS=0 True	(4) Public&Private Target IIS>0 True
Log(1+Export Product)$_t$	0.010**	0.017***		
	(0.005)	(0.006)		
Log(1+Export Product)$_{t-1}$			0.015***	0.019***
			(0.005)	(0.007)
Industry IIS	0.334*	0.434***	0.327*	0.427***
	(0.173)	(0.125)	(0.173)	(0.125)
Acquirer LogAsset	0.020***	0.025***	0.019***	0.026***
	(0.002)	(0.004)	(0.002)	(0.004)
Acquirer Leverage	-0.031*	-0.026	-0.033**	-0.028
	(0.016)	(0.034)	(0.016)	(0.034)
Acquirer Capex	-0.298***	-0.554**	-0.291***	-0.555**
	(0.091)	(0.218)	(0.092)	(0.217)
Acquirer Cash	-0.020	-0.140*	-0.019	-0.141*
	(0.032)	(0.077)	(0.032)	(0.077)
Acquirer Dividend	0.000	0.135	-0.002	0.135
	(0.137)	(0.247)	(0.137)	(0.247)
Acquirer TobinQ	0.004	-0.000	0.004	-0.001
	(0.003)	(0.006)	(0.003)	(0.006)
Acquirer ROA	0.097***	0.288***	0.097***	0.287***
	(0.027)	(0.058)	(0.027)	(0.058)
Cohort FE	Yes	Yes	Yes	Yes
SE Clustered (Cohort)	Yes	Yes	Yes	Yes
Observations	6,333	3,436	6,333	3,436
R-squared	0.086	0.122	0.087	0.121

Table 5. Pre-deal Supply Chain Labor Mobility, Imported Input Similarity, and the Likelihood of M&As

This table presents the coefficient estimates from the regressions that examine how the interaction effect between pre-deal supply-chain labor mobility and imported input similarity affects the likelihood of a merger. The sample is organized at the deal level (acquirer-target-announcement year level), which includes both actual and placebo deals. Each actual acquirer is paired with five placebo targets from the same SIC3 industry, selected based on the closest volume of imports to the actual target. Similarly, each actual target is matched with five placebo acquirers. The dependent variable, *True,* is a dummy variable that equals one for actual deals and zero for placebo deals. *Imported Input Similarity (IIS)* is the cosine similarity of the input products between the acquirer and the target. The test sample is partitioned based on whether IIS is larger than zero or equal to zero. The key independent variable, *HasSCMove*, is a dummy variable equal to one if, in the three years preceding the deal announcement, the acquirer/placebo acquirer hired at least one former employee of the target/placebo target who previously worked in a supply-chain–related role at the target/placebo target firm, and zero otherwise. Definitions of other independent variables are provided in Appendix I. Cohort fixed effects are included in all specifications. Robust standard errors, clustered at the cohort level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	Public&Private Target	Public&Private Target	Public Target	Public Target
	IIS>0	IIS=0	IIS>0	IIS=0
VARIABLES	True	True	True	True
HasSCMove	0.349***	0.272***	0.209***	0.102***
	(0.039)	(0.040)	(0.031)	(0.027)
Acquirer LogAsset	0.015***	0.017***	0.021***	0.023***
	(0.004)	(0.002)	(0.006)	(0.004)
Acquirer Leverage	-0.010	-0.033**	0.078*	-0.005
	(0.034)	(0.016)	(0.047)	(0.032)
Acquirer Capex	-0.571***	-0.303***	-0.106	-0.145
	(0.206)	(0.090)	(0.316)	(0.150)
Acquirer Cash	-0.134*	-0.032	-0.054	-0.029
	(0.078)	(0.032)	(0.107)	(0.066)
Acquirer Dividend	-0.080	-0.051	0.125	0.041
	(0.264)	(0.141)	(0.319)	(0.199)
Acquirer TobinQ	0.000	0.004	0.000	0.006
	(0.006)	(0.003)	(0.008)	(0.006)
Acquirer ROA	0.327***	0.096***	0.172*	0.050
	(0.058)	(0.027)	(0.091)	(0.044)
Difference	0.077*		0.107***	
Cohort FE	Yes	Yes	Yes	Yes
SE Clustered (Cohort)	Yes	Yes	Yes	Yes
Observations	3,436	6,333	1,392	1,694
R-squared	0.146	0.100	0.132	0.099

Table 6. Pre-deal Data Analyst Employment, Imported Input Similarity, and the Likelihood of M&As

This table presents the coefficient estimates from the regressions that examine how the interaction effect between pre-deal data analyst employment and imported input similarity affects merger likelihood. The sample is organized at the deal level (acquirer-target-announcement year level), which includes both actual and placebo deals. Each actual acquirer is paired with five placebo targets from the same SIC3 industry, selected based on the closest volume of imports to the actual target. Similarly, each actual target is matched with five placebo acquirers. The dependent variable, *True*, is a dummy variable that equals one for actual deals and zero for placebo deals. *Imported Input Similarity (IIS)* is the cosine similarity of the input products between the acquirer and the target. The test sample is partitioned based on whether *IIS* is larger than or equal to zero. The key independent variable, *Log(1+Num DA)*, is the natural logarithm of one plus the number of data analysts that the acquirer/placebo acquirer employs by the end of the year before the deal announcement. Definitions of other independent variables are provided in Appendix I. Cohort fixed effects are included in all specifications. Robust standard errors, clustered at the cohort level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	Public&Private Target	Public&Private Target	Public Target	Public Target
	IIS>0	IIS=0	IIS>0	IIS=0
VARIABLES	True	True	True	True
Log(1+Num DA)	0.013**	0.001	0.029***	-0.001
	(0.005)	(0.003)	(0.007)	(0.005)
Acquirer LogAsset	0.020***	0.020***	0.016**	0.027***
	(0.005)	(0.003)	(0.007)	(0.005)
Acquirer Leverage	-0.032	-0.033**	0.055	-0.002
	(0.034)	(0.016)	(0.049)	(0.032)
Acquirer Capex	-0.637***	-0.311***	-0.258	-0.135
	(0.213)	(0.090)	(0.325)	(0.154)
Acquirer Cash	-0.135*	-0.021	-0.043	-0.014
	(0.078)	(0.032)	(0.106)	(0.066)
Acquirer Dividend	0.052	-0.002	0.065	0.071
	(0.247)	(0.138)	(0.323)	(0.195)
Acquirer TobinQ	-0.004	0.004	-0.008	0.006
	(0.006)	(0.003)	(0.007)	(0.007)
Acquirer ROA	0.284***	0.098***	0.140	0.050
	(0.059)	(0.027)	(0.093)	(0.043)
Difference	0.012*		0.030***	
Cohort FE	Yes	Yes	Yes	Yes
SE Clustered (Cohort)	Yes	Yes	Yes	Yes
Observations	3,436	6,333	1,392	1,694
R-squared	0.117	0.085	0.118	0.094

Table 7. Import Related Mergers and Acquirers' Expansion of International Supply Chains After Deals

This table presents the coefficient estimates of regressions testing whether import-related mergers affect acquirers' likelihood of exporting from new suppliers and new sourcing countries. The sample is restricted to deals in the restricted sample described in Figure 1. In Panel A, *Num New Supplier* is the average number of new international suppliers the acquirer purchases from in the three-year period following the deal announcement, where new suppliers are defined as those that had no trade relationship with the acquirer before the deal announcement. *Num New Country* is the average number of new countries that the acquirer purchases from in the three-year period following the deal announcement, where new countries are defined as those that had no trade relationship with the acquirer before the deal announcement. *True* is a dummy variable that equals one for actual deals and zero for placebo deals. In Panel B, we carry out subgroup analysis based on whether *IIS* is larger or equal to zero. Cohort fixed effects are included in all specifications. Robust standard errors, clustered at the cohort level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Full Restricted Sample

	(1)	(2)
VARIABLES	Num New Supplier	Num New Country
True	8.588***	0.647***
	(1.335)	(0.111)
Acquirer LogAsset	3.929***	0.242***
	(0.417)	(0.029)
Acquirer Leverage	-0.252	-0.081
	(1.813)	(0.182)
Acquirer Capex	-36.392***	-1.321
	(9.357)	(1.158)
Acquirer Cash	-3.218	-0.805***
	(3.682)	(0.310)
Acquirer Dividend	-5.224	-2.040
	(14.776)	(1.398)
Acquirer TobinQ	0.232	0.079**
	(0.521)	(0.037)
Acquirer ROA	-2.496	0.621**
	(2.569)	(0.242)
Cohort FE	Yes	Yes
SE Clustered (Cohort)	Yes	Yes
Observations	2,097	2,097
R-squared	0.447	0.379

Panel B: Subgroups based on IIS between Acquirers and Targets

VARIABLES	(1) IIS>0 Num New Supplier	(2) IIS=0 Num New Supplier	(3) IIS>0 Num New Country	(4) IIS=0 Num New Country
True	9.188***	5.821***	0.544***	0.783***
	(2.497)	(1.607)	(0.188)	(0.159)
Acquirer LogAsset	6.018***	2.497***	0.305***	0.199***
	(0.909)	(0.468)	(0.056)	(0.038)
Acquirer Leverage	-5.534	-0.438	-0.548	0.097
	(5.354)	(1.792)	(0.462)	(0.206)
Acquirer Capex	-46.610	-32.655***	-1.357	-0.949
	(35.389)	(9.230)	(3.063)	(1.281)
Acquirer Cash	-6.388	-2.732	-1.862**	-0.496
	(10.966)	(3.105)	(0.798)	(0.337)
Acquirer Dividend	11.137	-3.768	-7.784**	-0.470
	(46.606)	(13.792)	(3.114)	(1.568)
Acquirer TobinQ	1.470	0.321	0.143	0.081**
	(1.557)	(0.441)	(0.113)	(0.038)
Acquirer ROA	-6.107	0.809	0.405	0.591**
	(9.745)	(2.538)	(0.828)	(0.271)
Difference	3.367**		-0.239	
Deal-cohort FE	Yes	Yes	Yes	Yes
Cluster at Deal-cohort Level	Yes	Yes	Yes	Yes
Observations	627	1,351	627	1,351
R-squared	0.543	0.385	0.453	0.405

Table 8. Acquirers' Likelihood of Importing from Targets' International Suppliers

This table presents the coefficient estimates of regressions testing whether import-related mergers affect acquirers' likelihood of importing from targets' international suppliers after deals. The sample is restricted to deals in the "restricted sample" described in Figure 1. In Panel A, *Buy* is a dummy variable that equals one if acquirer *i* imports from the target *j*'s supplier *s* in year *t*. *BuyExisting* is a dummy variable that equals one if acquirer *i* imports from the target *j*'s supplier *s* in year *t*, and the imported products consist of input goods that the acquirer previously imported before the deal. *BuyNew* is a dummy variable that equals one if acquirer *i* imports from the target *j*'s supplier *s* in year *t*, and the imported products include input goods not previously imported by the acquirer prior to the deal, but imported by other firms in the same SIC3 industry. *Post* is a dummy variable that equals one if the year is after the deal announcement year, and zero otherwise. *True* is a dummy variable that equals one for actual deals and zero for placebo deals. In Panel B, we carry out subgroup analysis based on the relationship duration between targets and their international suppliers, i.e., relationships≥3 years vs. relationships<3 years. In Panel C, we carry out subgroup analysis based on whether *IIS* is larger or equal to zero. Acquirer-target's supplier pair fixed effects and cohort-year fixed effects are included in all test specifications. Robust standard errors, clustered at the acquirer-target's supplier pair level, are reported in parentheses. ***, **, and * indicate the 1%, 5%, and 10% levels of statistical significance, respectively.

Panel A: Full Restricted Sample

VARIABLES	(1) Buy	(2) BuyNew	(3) BuyExisting
Post×True	0.042***	0.025***	0.024***
	(0.005)	(0.003)	(0.004)
Acquirer LogAsset	0.003**	0.001	0.002*
	(0.001)	(0.001)	(0.001)
Acquirer Leverage	0.003	-0.001	0.004
	(0.004)	(0.002)	(0.004)
Acquirer Capex	-0.014	-0.008	-0.000
	(0.013)	(0.008)	(0.011)
Acquirer Cash	0.001	-0.003	0.004
	(0.004)	(0.002)	(0.004)
Acquirer Dividend	-0.009	-0.008	-0.006
	(0.021)	(0.012)	(0.019)
Acquirer TobinQ	0.001**	0.000	0.001**
	(0.001)	(0.000)	(0.001)
Acquirer ROA	0.006**	0.001	0.006**
	(0.003)	(0.002)	(0.003)
Acquirer×Target's Supplier×Deal Cohort FE	Yes	Yes	Yes
Cohort×Year FE	Yes	Yes	Yes
SE Clustered (Acquirer×Target's Supplier)	Yes	Yes	Yes
Observations	127,798	127,366	127,798
R-squared	0.513	0.365	0.526

Panel B: Subgroups based on Target's Relationship Duration with International Suppliers

VARIABLES	(1) Duration>=3 Years Buy	(2) Duration<3 Years Buy	(3) Duration>=3 Years BuyNew	(4) Duration<3 Years BuyNew	(5) Duration>=3 Years BuyExisting	(6) Duration<3 Years BuyExisting
Post×True	0.077***	0.030***	0.035***	0.021***	0.050***	0.015***
	(0.011)	(0.005)	(0.006)	(0.003)	(0.010)	(0.004)
Acquirer LogAsset	0.005	0.002	0.004	0.001	0.003	0.002
	(0.003)	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)
Acquirer Leverage	-0.009	0.009*	-0.004	0.001	-0.004	0.006
	(0.008)	(0.005)	(0.004)	(0.003)	(0.008)	(0.004)
Acquirer Capex	0.023	-0.020	0.028	-0.017**	0.022	-0.003
	(0.036)	(0.014)	(0.021)	(0.008)	(0.031)	(0.012)
Acquirer Cash	0.007	-0.001	0.005	-0.007**	0.007	0.004
	(0.008)	(0.005)	(0.005)	(0.003)	(0.008)	(0.005)
Acquirer Dividend	-0.042	-0.003	-0.004	-0.014	-0.050	0.008
	(0.050)	(0.024)	(0.037)	(0.009)	(0.039)	(0.022)
Acquirer TobinQ	0.001	0.001**	0.000	0.000	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Acquirer ROA	0.004	0.007**	0.002	0.000	0.005	0.007**
	(0.007)	(0.003)	(0.005)	(0.002)	(0.006)	(0.003)
Difference	0.047***		0.014*		0.035***	
Acquirer×Target's Supplier×Deal Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustered (Acquirer×Target's Supplier)	Yes	Yes	Yes	Yes	Yes	Yes
Observations	34,167	93,442	34,116	93,059	34,358	93,463
R-squared	0.573	0.490	0.402	0.362	0.509	0.446

Panel C: Subgroups based on IIS between Acquirers and Targets

VARIABLES	(1) Buy IIS>0	(1) Buy IIS=0	(2) BuyNew IIS>0	(2) BuyNew IIS=0	(3) BuyExisting IIS>0	(3) BuyExisting IIS=0
Post×True	0.052***	0.028***	0.033***	0.013***	0.033***	0.012***
	(0.007)	(0.005)	(0.005)	(0.004)	(0.006)	(0.003)
Acquirer LogAsset	0.004	0.005**	0.003	0.002	0.004*	0.004*
	(0.003)	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)
Acquirer Leverage	0.012	0.008	-0.001	0.001	0.013*	0.005
	(0.009)	(0.006)	(0.005)	(0.003)	(0.008)	(0.005)
Acquirer Capex	-0.001	-0.018	-0.018	-0.013*	0.014	-0.004
	(0.030)	(0.014)	(0.015)	(0.008)	(0.028)	(0.011)
Acquirer Cash	0.004	0.007	-0.008	-0.002	0.006	0.008**
	(0.011)	(0.004)	(0.006)	(0.002)	(0.010)	(0.004)
Acquirer Dividend	-0.061	0.015	-0.006	-0.005	-0.077	0.020**
	(0.061)	(0.011)	(0.030)	(0.008)	(0.058)	(0.008)
Acquirer TobinQ	0.002*	0.000	0.001	0.000	0.002**	-0.000
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)
Acquirer ROA	0.012	0.002	0.003	-0.001	0.012*	0.002
	(0.007)	(0.003)	(0.005)	(0.002)	(0.007)	(0.002)
Acquirer×Target's Supplier×Deal Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustered (Acquirer×Target's Supplier)	Yes	Yes	Yes	Yes	Yes	Yes
Observations	66,102	61,061	66,102	61,061	66,102	61,061
R-squared	0.517	0.555	0.385	0.382	0.522	0.592

Table 9. Imported Input Similarity and Post-Deal Likelihood of Retaining Targets' Supply-Chain Talents

This table presents the coefficient estimates of regressions testing the interaction effect between imported input similarity and target employee career type on the likelihood. This test includes both actual mergers and acquisitions and placebo deals that pair actual acquirers with placebo targets. The test sample consists of all employees of target firms (actual and placebo ones) in the year of the deal announcement. The observations are organized at the acquirer-target-employee level. The dependent variable, *Leave3y*, is an indicator variable equal to one if the target employee leaves the target firm within three years after the deal announcement and does not move to any unit of the acquiring firm. (*Leave5y* is an indicator variable equal to one if the target employee leaves the target firm within five years after the deal announcement and does not move to any unit of the acquiring firm.) *SC_Role* is an indicator variable equal to one if the employee's job nature or job title is supply-chain related. Supply-chain related positions include roles such as purchasing managers, purchasing agents, buyers, supply chain managers, logisticians, logistics managers, procurement clerks, production planners and expediters, cargo and freight agents, customs brokers, and compliance officers involved in import/export or trade operations. Supply-chain-related job titles include those containing the terms "supply chain," "import," "supplier," "procure," or "purchasing". *True* is a dummy variable that equals one for actual deals and zero for placebo deals. *Positive IIS* is a dummy variable that equals one if *IIS* between the acquirer and the target is positive. Columns (1) and (3) include employees who have worked at the target firm for more than three years as of the year prior to the merger, while Columns (2) and (4) include employees who have worked at the target firm for less than three years. Definitions of other independent variables are provided in Appendix I. Cohort fixed effects are included in all specifications. Robust standard errors, clustered at the cohort level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) Experience>=3 years Leave3y	(2) Experience<3 years Leave3y	(3) Experience>=3 years Leave5y	(4) Experience<3 years Leave5y
SC_Role×True×Positive IIS	-0.015**	-0.008	-0.017**	-0.011
	(0.007)	(0.007)	(0.007)	(0.007)
SC_Role×Positive IIS	-0.003	-0.006	-0.007	-0.008
	(0.005)	(0.005)	(0.006)	(0.006)
True×Positive IIS	-0.002**	-0.003*	-0.003**	-0.004**
	(0.001)	(0.001)	(0.001)	(0.002)
SC_Role×True	-0.001	-0.000	-0.001	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Positive IIS	0.019***	0.010	0.021***	0.012*
	(0.007)	(0.007)	(0.007)	(0.006)
True	0.012***	0.013***	0.010***	0.010***
	(0.001)	(0.001)	(0.001)	(0.001)
SC_Role	0.038***	0.029***	0.041***	0.031***
	(0.009)	(0.010)	(0.010)	(0.011)
Deal Cohort FE	Yes	Yes	Yes	Yes
Cluster at Deal Cohort	Yes	Yes	Yes	Yes
Observations	3,376,242	2,759,465	3,376,242	2,759,465
R-squared	0.058	0.045	0.063	0.050

Table 10. Overlapping Supplier Base with Target's Product Market Rivals and Merger Likelihood

This table presents the coefficient estimates from the regressions that examine how acqruiers' overlapping supplier base with the target's product market rivals affects merger likelihood. The dependent variable, *True*, is a dummy variable that equals one for actual deals and zero for placebo deals. In Panel A, overlapping supplier base with target's product market rivals is captured by *RivalPurchaseVol* in columns (1) and (3), and *NumRivalPurchase* in columns (2) and (4). *RivalPurchaseVol* is the aggregated volume of goods purchased by the target's competitors from the acquirer's international suppliers in the year prior to the deal announcement year. *NumRivalPurchase* is the number of target's competitors that import from the acquirer's international suppliers in the year prior to the deal announcement year. In Panel B, these variables are interacted with *HighExp*, a dummy variable that is equal to one if the acquirer has maintained relationships with its international suppliers for three or more years. *Imported Input Similarity* (*IIS*) is the cosine similarity of the input products between the acquirer and the target. *Product Similarity* is Hoberg-Phillips TNIC3 product similarity score. Cohort fixed effects are included in all test specifications. Robust standard errors, clustered at the cohort level, are reported in parentheses. ***, **, and * indicate the 1%, 5%, and 10% levels of statistical significance, respectively.

Panel A. Unconditional Effect of Overlapping Supplier Base with Target's Product Market Rivals

	(1)	(2)	(3)	(4)
VARIABLES	True	True	True	True
RivalPurchaseVol	0.136***		0.113***	
	(0.027)		(0.027)	
NumRivalPurchase		0.001***		0.001***
		(0.000)		(0.000)
IIS	0.166***	0.160***	0.145**	0.139**
	(0.060)	(0.060)	(0.059)	(0.059)
Product Similarity	1.963***	1.976***	1.964***	1.972***
	(0.289)	(0.291)	(0.291)	(0.292)
Acquirer Controls	No	No	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
SE Clustered (Cohort)	Yes	Yes	Yes	Yes
Observations	3,183	3,183	3,175	3,175
R-squared	0.090	0.090	0.118	0.118

Panel B. Interaction Effect with Acquirer's Relationship Duration with International Suppliers

	(1)	(2)
VARIABLES	True	True
RivalPurchaseVol×HighExp	0.208***	
	(0.066)	
NumRivalPurchase×HighExp		0.002**
		(0.001)
HighExp	-0.081***	-0.077***
	(0.018)	(0.018)
RivalPurchaseVol	0.039	
	(0.032)	
NumRivalPurchase		0.000*
		(0.000)
Input Similarity	0.152***	0.145**
	(0.058)	(0.059)
Product Similarity	1.709***	1.700***
	(0.266)	(0.263)
Acquirer Controls	Yes	Yes
Cohort FE	Yes	Yes
SE Clustered (Cohort)	Yes	Yes
Observations	3,183	3,183
R-squared	0.128	0.127

Table 11. Importing Activities of Targets' Competitors after Mergers

This table presents the coefficient estimates of regressions examining the impact of import related mergers on the importing activities of targets' competitors after mergers. The sample is a panel data organized at acquirer-target-year level. The sample excludes the observations that indicate that the target's competitors have not imported from any of the acquirer's suppliers before the deal. The dependent variable, *NImport*, is the number of product market competitors of the target that import from the acquirer's international suppliers in the year. *Post* is a dummy variable that equals to one if the year is after the deal announcement year. *True* is a dummy variable that equals to one for actual deals and zero for placebo deals. *Log(NSup)* is the natural logarithm of the number of overseas suppliers of the acquirer. *Log(NRival)* is the natural logarithm of the number of product rivals of the target, as defined by the TNIC3 industry. *Log(Volume to Acq)* is the natural logarithm of the total import volume of the acquirer. Target-acquirer pair fixed effects are included in all test specifications. Definitions of other independent variables are provided in Appendix I. Robust standard errors, clustered at the target-acquirer pair level, are reported in parentheses. ***, **, and * indicate the 1%, 5%, and 10% levels of statistical significance, respectively.

	(1)	(2)	(1)	(2)
	OLS		**Poisson without fixed effects**	
	[dealyear-3, dealyear+3]	[dealyear-5, dealyear+5]	[dealyear-3, dealyear+3]	[dealyear-5, dealyear+5]
VARIABLES	NImport	NImport	NImport	NImport
Post×True	-0.835***	-0.689***	-0.292**	-0.302***
	(0.273)	(0.245)	(0.132)	(0.112)
Post	-	-	-0.143***	-0.102***
			(0.025)	(0.022)
True	-	-	0.147***	0.139***
			(0.027)	(0.023)
Log(NSup)	0.876***	1.031***	0.077***	0.094***
	(0.145)	(0.186)	(0.013)	(0.011)
Log(NRival)	1.875***	1.744***	0.899***	0.897***
	(0.135)	(0.097)	(0.010)	(0.008)
Log(Volume to Acq)	-0.025	-0.015	0.040***	0.033***
	(0.049)	(0.040)	(0.008)	(0.007)
Acquirer Controls	Yes	Yes	Yes	Yes
Target×Acquirer FE	Yes	Yes	No	No
Cohort×Year FE	Yes	Yes	No	No
SE Clustered (Target-Acquirer)	Yes	Yes	No	No
Observations	5,530	7,770	5,530	7,770
R-squared	0.859	0.801	0.859	0.801

Table 12. Foreclosure Effect and Operational Performance of Targets in Imported Related Mergers

This table presents the coefficient estimates of regressions examining the foreclosure effect of import related mergers on the operational performance of target firms. For this test, we only keep publicly traded target firms observed both before and after deal completion, i.e., our sample is restricted to actual targets that remain as standalone entities (i.e., not fully absorbed by their acquirers) that disclose independent financial statements. *Target Tobin Q* is the Tobin's Q of target firms; *Target LogSale* is the natural logarithm of total sales of target firms; *Target ROA* is the return on assets of target firms; and *Target Profit Margin* is the profit margin of target firms. Among the independent variables, RivalPurchaseVol is the aggregated volume of goods purchased by the target's competitors from the acquirer's suppliers in the year preceding the deal announcement year. *Post* is a dummy variable that equals to one if the year is after the deal announcement year. Definitions of other independent variables are provided in Appendix I. Target firm and year fixed effects are included in all test specifications. Robust standard errors, clustered at the target firm level, are reported in parentheses. ***, **, and * indicate the 1%, 5%, and 10% levels of statistical significance, respectively.

	(1)	(2)	(3)	(4)
	[T-3, T+3]	[T-3, T+3]	[T-5, T+5]	[T-5, T+5]
VARIABLES	Target Tobin Q	Target LogSale	Target ROA	Target Profit Margin
RivalPurchaseVol×Post	0.521***	0.058*	-0.007	-0.011
	(0.067)	(0.032)	(0.012)	(0.023)
Post	-0.080	-0.014	0.003	-0.039
	(0.115)	(0.054)	(0.025)	(0.071)
RivalPurchaseVol	-1.647	-2.701	-0.549	-2.586
	(3.723)	(1.667)	(1.222)	(2.016)
Target Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
SE Clustered (Target Firm)	Yes	Yes	Yes	Yes
Observations	267	267	267	262
R-squared	0.803	0.960	0.544	0.626

Appendix I. Variable Definitions

Dependent Variable

True	Indicator equal to one for actual deals and zero for placebo deals.
Buy	Indicator equal to one if the acquirer imports from the target's supplier in a given year.
BuyNew	Indicator equal to one if the acquirer imports new input products from the target's supplier that were not previously imported by the acquirer.
BuyExisting	Indicator equal to one if the acquirer imports input products from the target's supplier that were previously imported by the acquirer.
Num New Supplier	Average number of new international suppliers the acquirer purchases from within three years after the deal announcement.
Num New Country	Average number of new countries the acquirer purchases from within three years after the deal announcement.
Leave3(5)y	A dumy variable equal to one if the target employee leaves the target firm within three (five) years after the deal announcement and does not move to any unit of the acquiring firm.
RivalPurchaseVol	Aggregated volume of goods purchased by the target's competitors from the acquirer's suppliers in the year prior to the deal announcement year.
NumRivalPurchase	Number of the target's competitors that import from the acquirer's suppliers in the year prior to the deal announcement year.
NImport	Number of the target's product market competitors that import from the acquirer's suppliers in a given year.
Target Tobin Q	Tobin's Q of target firms that remain standalone and disclose independent financial statements.
Target LogSale	Natural logarithm of total sales of target firms.
Target ROA	Return on assets of target firms.
Target Profit Margin	Profit margin of target firms.

Independent Variable

Imported Input Similarity	Cosine similarity of the imported input products between the acquirer and the target.
Supplier Similarity	Cosine similarity of the overseas supplier base between the acquirer and the target.
Product Similarity	Hoberg-Phillips TNIC3 product similarity score.
Industry Imported Input Similarity (Industry IIS)	Average similarity between the target's import vector and that of the acquirer's TNIC3 industry peers.
China Imported Input Similarity (China IIS)	Cosine similarity between the acquirer's inputs imported from China and the target's inputs not imported from China.

HighExp	Indicator equal to one if the acquirer has maintained relationships with international suppliers for at least three years.
SC Risk	Firm-level supply chain risk following Ersahin, Giannetti, and Huang (2024).
Economy SC Risk	Economy-wide supply chain risk measured as the average firm-level supply chain risk in a given year.
Trade Policy Uncertainty	Trade Policy Uncertainty Index from Caldara et al. (2020).
Log(1+Export Volume)	Natural logarithm of one plus the total export volume of the acquirer.
Log(1+Export Country)	Natural logarithm of one plus the number of countries the acquirer exports to.
Log(1+Export Product)	Natural logarithm of one plus the number of products the acquirer exports.
HasSCMove	A dummy variable that equals to one if there is at least one target's supply chain employee move to the acquirer within three years prior to the deal announcement year.
Log(1+Num DA)	Natural logarithm of one plus the number of data analysts that the acquirer employs by the end of the year before deal announcement.
SC_Role	A dummy variable equal to one if the employee's job nature or job title is supply-chain related.
LogAsset	Natural logarithm of the total assets of the firm.
Leverage	Total liabilities divided by total assets.
Capex	Capital expenditure divided by total assets.
Cash	Cash holdings divided by total assets.
Dividend	Total dividends divided by total sales.
Tobin Q	Market value of equity divided by the book value of equity.
ROA	Return on assets (net income divided by total assets).

Appendix Tables

Table A1. Imported Input Similarity and The Likelihood of Mergers: Horizontal Deals within the Same Industry

In Panel A, we report results for the same test specification as in Panel A of Table 2. Columns (1) and (3) report results for the deals in which both acquirer and target are in the same industry, as identified by SIC 3-digit code, while Columns (2) and (4) report results for deals in which they are in different industries. In Panel B, we replicate the results reported in Table 3 for the deals in which both acquirer and target are in the same industry, as identified by SIC 3-digit code. Cohort fixed effects are included in all specifications. Robust standard errors, clustered at the cohort level, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Columns (1) and (3) of Table 2

	(1)	(2)	(3)	(4)
	Public&Private Target	Public&Private Target	Public Target	Public Target
	Same Industry	Different Industry	Same Industry	Different Industry
VARIABLES	True	True	True	True
IIS	0.213***	0.309***	0.151**	0.131
	(0.051)	(0.060)	(0.069)	(0.099)
Supplier Similarity	0.612**	0.662**	0.073	0.221
	(0.242)	(0.277)	(0.361)	(0.342)
Product Similarity			1.886***	2.707***
			(0.328)	(0.498)
Acquirer LogAsset	0.024***	0.026***	0.027***	0.034***
	(0.003)	(0.002)	(0.004)	(0.004)
Acquirer Leverage	-0.015	-0.023	0.047	0.021
	(0.022)	(0.018)	(0.033)	(0.036)
Acquirer Capex	-0.165	-0.594***	-0.020	-0.539**
	(0.120)	(0.104)	(0.154)	(0.229)
Acquirer Cash	-0.042	-0.033	-0.061	0.027
	(0.040)	(0.037)	(0.059)	(0.095)
Acquirer Dividend	-0.032	0.032	0.085	0.093
	(0.152)	(0.163)	(0.201)	(0.263)
Acquirer TobinQ	0.004	0.007*	0.004	0.001
	(0.005)	(0.004)	(0.006)	(0.007)
Acquirer ROA	0.105***	0.145***	0.060	0.112**
	(0.038)	(0.026)	(0.055)	(0.051)
Difference	-0.096 (not significant)		-0.020 (not significant)	
Cohort FE	Yes	Yes	Yes	Yes
SE Clustered (Cohort)	Yes	Yes	Yes	Yes
Observations	4,079	5,938	1,640	1,543
R-squared	0.050	0.057	0.120	0.107

Panel B: Replication of Table 3 for Horizontal Deals within the Same Industry

VARIABLES	(1) Public&Private Target Same Industry True	(2) Public&Private Target Different Industry True	(3) Public Target Same Industry True	(4) Public Target Different Industry True
IIS×SC Risk$_{t-1}$	0.001	0.004	0.019**	0.005**
	(0.006)	(0.005)	(0.009)	(0.002)
IIS	0.235***	0.345***	0.158	0.170
	(0.070)	(0.081)	(0.101)	(0.146)
SC Risk$_{t-1}$	-0.000	0.000	-0.003***	-0.000
	(0.000)	(0.000)	(0.001)	(0.000)
Supplier Similarity	0.720***	0.719***	0.593*	0.274
	(0.264)	(0.221)	(0.314)	(0.434)
Product Similarity			2.323***	3.329***
			(0.483)	(0.681)
Acquirer LogAsset	0.021***	0.031***	0.017***	0.040***
	(0.005)	(0.004)	(0.006)	(0.006)
Acquirer Leverage	0.001	-0.066**	0.124**	0.034
	(0.034)	(0.026)	(0.051)	(0.060)
Acquirer Capex	-0.004	-0.785***	0.196	-1.025***
	(0.206)	(0.158)	(0.304)	(0.352)
Acquirer Cash	-0.127**	-0.051	-0.119	0.123
	(0.055)	(0.058)	(0.090)	(0.148)
Acquirer Dividend	0.238	0.124	0.326	-0.017
	(0.227)	(0.240)	(0.296)	(0.381)
Acquirer TobinQ	-0.008	0.005	-0.010	-0.006
	(0.007)	(0.005)	(0.008)	(0.010)
Acquirer ROA	0.115	0.156***	0.122	0.222*
	(0.072)	(0.048)	(0.105)	(0.120)
Cohort FE	Yes	Yes	Yes	Yes
SE Clustered (Cohort)	Yes	Yes	Yes	Yes
Observations	2,640	4,210	1,066	1,090
R-squared	0.074	0.076	0.169	0.145

Table A2 Import Related Mergers, Past Export Activities, and Acquirers' Expansion of International Supply Chains After Deals

This table presents the coefficient estimates of regressions testing whether the interaction effect between import related mergers and previous export activities affect acquirers' likelihood of exporting from new suppliers after deal announcements. The sample is restricted to deals in the restricted sample described in Figure 1. *Num New Supplier* is the average number of new international suppliers the acquirer purchases from in the three-year period following the deal announcement, where new suppliers are defined as those that had no trade relationship with the acquirer before the deal announcement. *True* is a dummy variable that equals one for actual deals and zero for placebo deals. Cohort fixed effects are included in all specifications. *Log(1+Export Volume)* is the natural logarithm of one plus its export volume; *Log(1+Export Country)* is the natural logarithm of one plus the number of countries it exports to, and *Log(1+Export Product)* is the natural logarithm of one plus the number of products it exports to other countries. Robust standard errors, clustered at the cohort level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) Num New Supplier	(2) Num New Supplier	(2) Num New Supplier
True×Log(1+Export Volume)	5.419***		
	(1.794)		
True× Log(1+Export Country)		1.670**	
		(0.701)	
True× Log(1+Export Product)			3.339**
			(1.311)
True	5.624***	5.865***	5.815***
	(1.337)	(1.328)	(1.325)
Log(1+Export Volume)	1.312***		
	(0.333)		
Log(1+Export Country)		4.626***	
		(0.982)	
Log(1+Export Product)			3.619***
			(0.697)
Acquirer LogAsset	3.550***	3.452***	3.400***
	(0.399)	(0.398)	(0.396)
Acquirer Leverage	0.005	0.259	0.165
	(1.809)	(1.789)	(1.802)
Acquirer Capex	-27.072***	-27.201***	-25.222**
	(9.835)	(9.825)	(9.809)
Acquirer Cash	-3.269	-3.579	-3.237
	(3.547)	(3.571)	(3.509)
Acquirer Dividend	-11.095	-11.451	-10.102
	(14.211)	(14.202)	(14.197)
Acquirer TobinQ	0.366	0.362	0.381
	(0.511)	(0.510)	(0.504)
Acquirer ROA	-1.275	-0.964	-0.679
	(2.460)	(2.461)	(2.424)
Cohort FE	Yes	Yes	Yes
SE Clustered (Cohort)	Yes	Yes	Yes
Observations	2,097	2,097	2,097
R-squared	0.471	0.474	0.479

Table A3. New International Suppliers of Acquirers: Using Withdrawn Deals as Placebos

This table presents estimates from regressions examining the impact of import-related mergers (IRMs) on acquirers' establishment of new supply-chain relationships with international suppliers. The dependent variable, *Num New Supplier*, is the average number of suppliers that begin importing to the acquirer in the three years following the deal, having had no prior import relationship with the acquirer. Withdrawn deals in this test are selected based on the following screening criteria: (1) The deal must be classified as a merger, acquisition of majority interest, or acquisition of assets; (2) The transaction value must exceed $1 million; (3) Deals involving firms in the financial sector (SIC 6000–6999) are excluded; (4) The acquirer must be a publicly listed firm; and (5) Both the acquirer and target must have import records in the Panjiva database (available from 2007 onward) in the year prior to the deal announcement. We pair these withdrawn deals with true deals following Bena and Li (2014), using the following criteria: (1) occur in acquirer–target industry pairs (based on SIC2 codes) matching those of the withdrawn deals; (2) are announced within a five-year window centered on the announcement year of the corresponding withdrawn bids; and (3) has the closest acquirer size (total assets) with the withdrawn deal. *True* is a dummy variable that is equal to one when the deal is an actual deal (instead of a withdrawn deal). *Imported Input Similarity* (*IIS*) measures the cosine similarity of input products between the acquirer and the target. *Import Volume* is the import volume of the acquirer. Both *IIS* and *Import Volume* are measured in the year before the deal announcement. Deal-Year fixed effects are included in all specifications. Robust standard errors, clustered at the 2-digit SIC industry level, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) Num New Supplier	(2) Num New Supplier
True×IIS		70.122**
		(30.284)
True	8.645**	18.002***
	(3.445)	(3.169)
True×Import Volume		-0.019***
		(0.004)
IIS	29.347	7.775
	(19.649)	(17.099)
Import Volume	0.001	0.018***
	(0.002)	(0.004)
Acquirer LogAsset	2.268	0.166
	(2.863)	(2.172)
Acquirer Leverage	7.429	1.508
	(13.636)	(12.902)
Acquirer Capex	9.983	24.487
	(35.387)	(38.674)
Acquirer Cash	-19.299	-33.467
	(26.055)	(25.311)
Acquirer Dividend	31.846	83.611*
	(121.572)	(41.839)
Acquirer TobinQ	-2.387	-0.641
	(2.638)	(2.711)
Acquirer ROA	-11.326	-15.127
	(12.880)	(10.305)
Deal Year FE	Yes	Yes
SE Clustered (SIC 2-digit Industry)	Yes	Yes
Observations	77	77
R-squared	0.207	0.548

Table A4. Acquirers' Likelihood of Importing from Targets' International Suppliers: Using Withdrawn Deals as Placebos

This table presents the coefficient estimates of regressions testing whether import-related mergers affect acquirers' likelihood of importing from targets' international suppliers after deals, using withdrawn deals as placebos. The sample includes withdrawn deals and their matched actual deals in the "restricted sample" at the deal–acquirer-target's pre-existing supplier level. *Buy* is a dummy variable that equals one if acquirer *i* imports from the target *j*'s supplier *s* in year *t*. *BuyExisting* is a dummy variable that equals one if acquirer *i* imports from the target *j*'s supplier *s* in year *t*, and the imported products consist of input goods that the acquirer previously imported before the deal. *BuyNew* is a dummy variable that equals one if acquirer *i* imports from the target *j*'s supplier *s* in year *t*, and the imported products include input goods not previously imported by the acquirer before the deal, but imported by other firms in the same SIC3 industry. *Post* is a dummy variable that equals one if the year is after the deal announcement year, and zero otherwise. *True* is a dummy variable that equals one for actual deals and zero for withdrawn deals. Acquirer-target's supplier pair fixed effects and cohort-year fixed effects are included in all test specifications. Robust standard errors, clustered at the acquirer-target's supplier pair level, are reported in parentheses. ***, **, and * indicate the 1%, 5%, and 10% levels of statistical significance, respectively.

VARIABLES	(1) Buy	(2) BuyNew	(3) BuyExisting
Post×True	0.054***	0.036***	0.026**
	(0.015)	(0.012)	(0.011)
Post	-0.018**	-0.001	-0.009
	(0.008)	(0.004)	(0.008)
Acquirer LogAsset	-0.009	-0.010	-0.004
	(0.011)	(0.006)	(0.010)
Acquirer Leverage	0.056*	0.016	0.032
	(0.031)	(0.021)	(0.027)
Acquirer Capex	-0.395	-0.447**	-0.179
	(0.298)	(0.187)	(0.246)
Acquirer Cash	0.032	0.059***	0.000
	(0.032)	(0.021)	(0.029)
Acquirer Dividend	-0.649***	-0.432***	-0.499**
	(0.213)	(0.132)	(0.197)
Acquirer TobinQ	0.006	0.001	-0.000
	(0.007)	(0.005)	(0.007)
Acquirer ROA	0.130***	0.068*	0.056
	(0.049)	(0.038)	(0.042)
Acquirer×Target's Supplier×Deal Cohort FE	Yes	Yes	Yes
Cohort×Year FE	Yes	Yes	Yes
SE Clustered (Acquirer×Target's Supplier)	Yes	Yes	Yes
Observations	5,157	5,157	5,157
R-squared	0.523	0.331	0.547

Table A5. **Acquirers' Likelihood of Importing from Their Existing International Suppliers**

This table presents the coefficient estimates of regressions testing whether import-related mergers affect acquirers' likelihood of importing from their existing international suppliers after deals. The sample is organized at the deal–acquirer–pre-existing supplier–year level and includes only suppliers from whom the acquirer had imported prior to the merger. *Buy* is a dummy variable equal to one if the acquirer imports from its existing international supplier in a given year. *Post* is a dummy variable that equals one if the year is after the deal announcement year, and zero otherwise. *True* is a dummy variable that equals one for actual deals and zero for placebo deals. *Imported Input Similarity* (*IIS*) measures the cosine similarity of input products between the acquirer and the target. Cohort-Acquirer-Acquirer's Supplier fixed effects and year fixed effects are included in all test specifications. Robust standard errors, clustered at the cohort-acquirer level, are reported in parentheses. ***, **, and * indicate the 1%, 5%, and 10% levels of statistical significance, respectively.

VARIABLES	(1) Buy	(2) Buy
Post×True×IIS		-0.035**
		(0.014)
Post×IIS		-0.038***
		(0.010)
Post×True	-0.010***	-0.006***
	(0.002)	(0.002)
Post	-0.098***	-0.096***
	(0.002)	(0.002)
Acquirer LogAsset	0.067***	0.067***
	(0.002)	(0.002)
Acquirer Leverage	-0.018**	-0.014*
	(0.008)	(0.008)
Acquirer Capex	0.178***	0.170***
	(0.042)	(0.042)
Acquirer Cash	-0.098***	-0.097***
	(0.013)	(0.013)
Acquirer Dividend	-0.375***	-0.354***
	(0.051)	(0.051)
Acquirer TobinQ	-0.005***	-0.006***
	(0.001)	(0.001)
Acquirer ROA	-0.095***	-0.092***
	(0.010)	(0.010)
Cohort-Acquirer-Acquirer's supplier FE	Yes	Yes
Year FE	Yes	Yes
SE Clustered (Cohort-Acquirer)	Yes	Yes
Observations	685,469	685,469
R-squared	0.381	0.381

Online Appendix Tables

Table OA1. Industry Imported Input Similarity, Supply Chain Risks, and The Likelihood of Mergers: Zero Imported Input Similarity Sample

This table reports the coefficients of regressions that examine the effects of industry imported input and supply-chain risks on merger likelihood. The sample only includes those deals with zero *Imported Input Similarity*. We use acquirer-specific supply chain risks measure following Ersahin, Giannetti, and Huang (2024). The test specifications in this table follow those in Table 2, where the dependent variable, *True*, equals one for actual deals and zero for placebo deals. *Industry Imported Input Similarity* (*IIS*) average similarity between the target's import vector and that of the peer firms of the acquirer in its TNIC3 industry in the year preceding the merger. *Industry IIS* is interacted with each supply chain risk measure. Cohort fixed effects are included in all specifications. Robust standard errors, clustered at the cohort level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	Public&Private Target	Public Target	Public Target	Public&Private Target
	IIS=0	IIS=0	IIS=0	IIS=0
VARIABLES	True	True	True	True
Industry IIS×SC Risk$_{t-1}$			0.000	0.001
			(0.000)	(0.001)
Industry IIS	0.335*	0.034	0.350	-0.024
	(0.173)	(0.215)	(0.396)	(0.542)
SC Risk$_{t-1}$			0.000	-0.000
			(0.000)	(0.000)
Acquirer LogAsset	0.021***	0.027***	0.024***	0.029***
	(0.002)	(0.004)	(0.004)	(0.006)
Acquirer Leverage	-0.032**	-0.002	-0.036	0.069
	(0.016)	(0.032)	(0.026)	(0.046)
Acquirer Capex	-0.318***	-0.136	-0.332**	-0.205
	(0.090)	(0.154)	(0.151)	(0.294)
Acquirer Cash	-0.020	-0.014	-0.077	-0.002
	(0.032)	(0.066)	(0.050)	(0.117)
Acquirer Dividend	0.004	0.072	-0.134	-0.319
	(0.137)	(0.195)	(0.209)	(0.343)
Acquirer TobinQ	0.004	0.006	0.001	-0.001
	(0.003)	(0.007)	(0.005)	(0.009)
Acquirer ROA	0.095***	0.050	0.098*	0.186**
	(0.027)	(0.044)	(0.051)	(0.086)
Cohort FE	Yes	Yes	Yes	Yes
SE Clustered (Cohort)	Yes	Yes	Yes	Yes
Observations	6,333	1,694	4,052	1,036
R-squared	0.086	0.094	0.115	0.121