Input Similarity, Core Competencies and M&As

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Abstract

The resource-based view holds that firms diversify to utilize core competencies. We contend that firms' know-how in input usage, or input capability, is a key component of the core competencies and study its implications for mergers and acquisitions. We infer input capability based on the relative input share, and argue that firms can transform their input capability to another industry with similar input usage. We find that firms, when entering new industries through acquisitions, are more likely to target firms with more similar inputs. Utilizing China's WTO entry which lowered import tariffs as a natural experiment, we find that firms are more likely to acquire targets from other industries with larger tariff reductions in their common inputs. Furthermore, the effects are more salient when affected inputs are differentiated or innovation-intensive.

1 Introduction

According to the resource-based view of the firm, firms possess different inalienable and scarce resources or capabilities, that lead to competitive edge and drive business success (Wernerfelt, 1984; Prahalad and Hamel, 1990; Barney, 1991). These resources form the core competencies of a firm and play an important role in shaping the boundary of the firm (Chandler, 1962). More specifically, knowledge about input usage in the incumbent industry, or input capability could be one key element underlying the core competencies of the firm. Since Penrose (1955), the literature

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†*Acknowledgment*: We benefitted from discussions with participants of the 2022 HKU Trade and Development Workshop, and Seminars in IESR, and WHU.

has long recognized that firms can go beyond the limits imposed by the size of a single industry by entering new industries. Firms, therefore, could gain economies of scope by diversifying into industries with common inputs so their "core competencies" can be fruitfully utilized. This idea was provided early by Lemelin (1982) and recently revived by Boehm et al. (2022) to study firm diversifications or internal growth.[1] In this paper, we recall the classic resource-based view of the firm and borrow this insight to understand mergers and acquisitions (M&As).[2] Specifically, we show that the know-how embedded in common input usage is a key determinant for mergers involving parties outside of horizontal or vertical relationships, also known as diversifying deals.[3]

We define and infer a firm's input capability based on the relative input share in its incumbent industry, measured using the input-Output (IO) table, as in Lemelin (1982) and Boehm et al. (2022). The input capability is more likely to be transferable among two industries with a higher degree of common input usage, measured as the similarity score of the input share of these two industries.[4] Using the sample of diversifying or conglomerate mergers, which are mergers excluding horizontal and vertical ones, of Chinese firms from 1998 to 2007 obtained from SDC Platinum, we first look at how the propensity and number of merger deals between any given pair of industries are associated with the degree of common input usage between them. We find a positive and significant correlation between input similarity and M&As. This pattern is evident from a bin-scatter plot where we plot the input similarity of industry pairs into twenty bins, against the pair-wise merger propensities, as shown in Figure 1. We also verify such a relationship in OLS regressions further controlling for the industry-by-year fixed effects of both the acquirer and target industries.[5] The

[1] Lemelin (1982) shows, in a correlational sense, that firms are more likely to operate in different industries when the industries share similar input usage. Boehm et al. (2022) provide causal evidence that Indian plants are more likely to produce goods in a new industry with similar inputs to incumbent goods, using the de-reservation of input industries as a natural experiment.

[2] According to Chen et al. (2022), the combined Google Scholar citation count for Wernerfelt (1984), Prahalad and Hamel (1990), and Barney (1991) is over 150,000, and the resource-based view of the firm is a hugely influential literature that forms a core part of MBA and executive education syllabi, and thus is salient to many decision makers on M&As.

[3] Diversifying deals account for a significant share in M&As. Taking China for example, in our sample period, 1998-2007, 56% M&As are diversifying deals. Similar case is found in the US, where the diversifying deals account for 47% of all M&As during 1978-2019 (Jia and Sun, 2022).

[4] More specifically, for each industry, we know its cost share (i.e., input usage out of total input usage) of any input industry. The input usage structure of a given industry can then be represented as a vector of the industry's cost share. The similarity or inner product of any two industry's cost share vector can therefore be used to measure how similar two industries are in terms of their input usage structure.

[5] Directly controlling for the acquirer industry by year, and target industry by year fixed effects allows us to tease out time-varying changes common to a given industry. For example, industries could be facing disparate situations

economic magnitude is substantial, a one standard deviaion increase in input similarity will raise the propensity of merger deals by about 30% of the average mean. We also directly control for the output similarity of the two industries and find the inference remains unchanged.

However, the positive correlation we uncovered may not be necessarily causal. Industry pairs with a higher level of common input usage could also be more similar in various other dimensions such as technology, human capital profiles, and so on, which have been shown to facilitate synergistic gains and merger activities in general (Rhodes-Kropf and Robinson, 2008) and thus, the result could be subject to omitted-variable bias.[6] Indeed, the existing evidence in the M&A literature on how the similarity between certain firm characteristics is associated with higher merger likelihood is mainly correlational and faces exactly the same empirical challenge.[7]

Our work advances the literature by providing causal evidence that overcomes the aforementioned empirical challenge. To accomplish this, we use China's WTO accession as a natural experiment. As a result of China fulfilling the entry requirement of WTO, the tariff rates for a wide range of intermediate input industries were greatly reduced in a way that has been treated as close to exogenous in the literature (Brandt et al., 2017). Economic theory and empirical evidence show that industries with more tariff reductions on their inputs use a greater quantity, a broader variety, and a higher quality of these inputs.[8] As a result, in the same vein as Boehm et al. (2022), we can make use of the tariff reductions brought about by the WTO entry to generate exogenous variations in input similarity across industry pairs and conduct a difference-in-differences empirical analysis. The treatment group includes industry pairs that have a higher ex-ante level of common input usage and also have a substantial reduction in input tariffs. As a result, they enjoyed a larger increase in the input similarity due to China's WTO entry.[9] The remaining industry pairs, which witness a lower increase in the common input usage, constitute the control group. As a result, we

in the competitive environment or export opportunities due to WTO entry.

[6]For example, due to clustering, industries with similar inputs could be located in nearby regions, thus there could be common regional shocks that correlate with the merger activities. Industries with similar inputs could also have similar labor skill profiles, thus nationwide changes in the structure of the labor force such as the college enrollment expansion started in 1999 could also have an effect.

[7]The growing list of papers includes product similarity (Hoberg and Phillips, 2010), technology overlap (Bena and Li, 2014), human capital relatedness (Lee et al., 2018), and cultural similarity (Bereskin et al., 2018).

[8]See, for example, Amiti and Konings (2007); Goldberg et al. (2010); Topalova and Khandelwal (2011); Bas and Strauss-Kahn (2015); Fan et al. (2015); Fieler et al. (2018).

[9]We confirm that this is indeed the case, using the change in China's Input-Output Table from 2002 to 2007 and results are presented in appendix table A3.

can compare the change in the merger proclivity for these two groups of industry pairs, before and after China's WTO entry. The findings support our hypothesis: industry pairs with more ex-ante similar inputs and higher tariff reductions as a result of WTO accession are significantly more likely to conduct M&A among themselves.

An important identifying assumption behind our difference-in-differences empirical design is that, had China not joined the WTO in 2001, there would be no differential trends in merger activities between these two groups of industry pairs. While this assumption is not testable, we provide corroborative evidence by conducting the dynamic analysis, and find that our treatment and control groups have similar trends in merger dynamics before the 2001 WTO entry. Our results are also robust to controlling for the import tariff shocks for the common outputs, as well as the trade policy uncertainty shocks from the US. We further conduct a set of robustness checks including perturbing the threshold in dropping industry pairs with potential vertical relationship, defining diversifying deals using a more aggregated industry classification, and using the cosine similarity measure to capture input similarity. Our findings are invariant to these tests.

We further exploit the characteristics across inputs to shed light on the mechanism that it is the *core competencies* in input usages that drives our findings. Core competencies rely on resources that are costly to acquire outside the firm (Penrose, 1955; Chandler, 1962), therefore, in terms of input usage, they should matter more for specific inputs (Nunn, 2007; Barrot and Sauvagnat, 2016).[10] We use three alternative measures of input specificity. The first one is the Rauch (1999) classification of differentiated vs. homogeneous goods. Second, we use the industry average R&D expenditure shares to capture the know-how imbedded in each input. Lastly, we use the industry average patent intensity, measured by the total patent counts over total sales.[11] We find that the causal effects of input similarity on merger activities are significantly stronger when the common inputs are more specific, consistent with our contention that capabilities in input usages are behind firms' core competencies.

Our work contributes primarily to the M&A literature. M&As are among the most important

[10]Non-specific inputs are in general more substitutable and used by more industries. Expertise in using them tends to be common knowledge that is exchangeable outside the firm's boundary, making it less likely to constitute the firm's core competencies.

[11]We also confirm that the degree of tariff reductions do not systematically vary with our measures of input specificity, so that we capture effects from different input specificity conditional on the level of tariff reductions.

types of corporate investment activities and bear critical implications for the efficient reallocation of resources in the economy.[12] More specifically, we contribute to a growing literature that understand the determinants behind deals outside of horizontal or vertical relationships, also known as diversifying or conglomerate deals. Existing literature demonstrates that determinants of such merger deals include asset complementarity due to product similarity (Hoberg and Phillips, 2010), technology overlap (Bena and Li, 2014), human capital relatedness (Lee et al., 2018), and cultural similarity (Bereskin et al., 2018) between the acquirers and targets. While these works mainly show correlational evidence, we are able to provide causal evidence based on a difference-in-differences empirical design that exploits China's WTO entry as a quasi natural experiment.

Our work is particularly relevant to the literature that uncovers merger motives related to the efficiency gains, or cost reductions.[13] The merger motive that we argue fits into these studies on several fronts. First, Horn and Wolinsky (1988) show that firms benefit from a merger by increasing their bargaining power toward suppliers to reduce the input price. In studying mergers in the paper industry, Pesendorfer (2003) finds a higher efficiency gain in cost and conjectures that one of the cost savings induced by mergers could be the more efficient allocation of inputs. In studying the lodging industry, Kalnins et al. (2017) show that merging firms could enjoy a lower marginal cost due to the increased size of common inputs, or the increased capacity utilization when their outputs face stochastic but independent demand. Our finding that input similarity increases mergers is in line with these motives as common input usage allows the merged entities to better exploit those benefit. Second, we argue that firms' know-how of their input usage could be an important element of core competencies that can be transferred to firms in distinct industries and lead to efficiency gains. Bloom et al. (2012) show that US firms can transplant their superior usage of IT to their acquired establishments in UK. Apparently, firms' capabilities in the usage of production inputs do not have to be confined to IT and we show that this know-how transplant is especially the case for specific inputs that are differentiated, or knowledge-intensive.

Our work also contributes to the strategy and management literature on the resource-based

[12] Evidence shows that M&As affect employment (Geurts and Van Biesebroeck, 2019), improve plant-level productivity (McGuckin and Nguyen, 1995; Maksimovic and Phillips, 2001; Schoar, 2002; Harris et al., 2005) and profitability (Braguinsky et al., 2015), and aid the diffusion of new technologies (Jovanovic and Rousseau, 2008).

[13] Another notable source of efficiency gains or synergies is the scale economies in production, as in the case of brewing industry (Grieco et al., 2018), and lodging industry (Kalnins et al., 2017).

theory of the firm (Wernerfelt, 1984; Prahalad and Hamel, 1990; Barney, 1991). As pointed out by Chen et al. (2022), this is a hugely influential literature that forms a core part of MBA and executive education, and thus salient to decision makers of M&A. Our paper is closely related to Boehm et al. (2022), who study how input similarity can explain the new product introductions at the plant level. While both papers share a common theme, there are significant differences. First, we explore and find that specific inputs matter much more in the effect of common input capabilities. Second, in our setting of M&As, the acquirer can not only transfer its core capabilities in input usage from its industry to the target, but also can receive such a transfer from the target firm. This two-way feedback effect is absent in the case of a firm's organic growth such as Boehm et al. (2022): when a plant offers a new product, it could only rely on its own capabilities. At the same time, our paper is also consistent with a broader literature that emphasizes asset complementarity and synergy creation in M&As (Rhodes-Kropf and Robinson, 2008).

Lastly, our work contributes to the literature of international trade and trade policies [14] More specifically, a strand of the literature documents substantial productivity and growth enhancing role of trade liberalization in intermediate inputs, as imported inputs have been found to improve firm productivity, increase product scope and quality, promote innovation, and facilitate firms' exports.[15] In particular, we join a small but growing works such as Breinlich (2008) and Liu et al. (2019) that study how trade policies could have an aggregate productivity effect, by promoting resource allocations through mergers and acquisitions activities. While these two papers examine the impact on horizontal and vertical industries, respectively, our paper complements them and studies mergers among different industries (i.e., conglomerate mergers) that share similar inputs.

[14] The trade literature currently adopts a narrower scope of 'core competency' and uses it to refer to the core product that a firm can produce with least marginal cost. This assumption has been widely used in models of multiproduct firms such as Eckel and Neary (2009), Mayer et al. (2014), and Arkolakis et al. (2021). A large empirical literature also differentiates between core products and peripheral products, for example, Bernard et al. (2011), Ma et al. (2014), and Manova and Yu (2017). However, as pointed out by Ding (2023), such a modelling approach precludes cost or input complementarity from multi-industry operations and can be restrictive.

[15] See, for example, Amiti and Konings (2007); Goldberg et al. (2010); Topalova and Khandelwal (2011); Bas and Strauss-Kahn (2015); Fan et al. (2015); Feng et al. (2016); Liu and Qiu (2016); Fieler et al. (2018).

2 Data and Variables

The merger data comes from Thomson Reuters SDC Platinum (SDC). This database contains deal-level data from worldwide M&A transactions involving at least 5% ownership of the target and a transaction value of one million US dollars or more, or where the transaction value is unknown. The database contains information of targets and acquirers such as firm name, country, industry, parent firm, primary business, and key financial characteristics. It also includes information of each M&A transaction such as the announcement time, completion status, time to completion, value of transaction, and transaction share. Our research focuses on domestic M&As in China, so we extract all transactions from the SDC database that have both the acquirer and target countries listed as China (excluding Hong Kong, Macao, and Taiwan for the sake of pure "domestic firms" by convention). To be consistent with the similarity measures, the industry is defined at the Chinese Input-Output (IO) industry level. As a result, each firm is assigned to an IO industry based on its primary industry classification at the SIC four-digit level designated by SDC.

Our dataset contains all *completed* Chinese domestic mergers from 1998 to 2007. We choose 2007 as the end year of the sample period to avoid the confounding effects of the global financial crisis. We use the Chinese IO Table in 2002 to classify industries. The IO table is published by the National Bureau of Statistics of China every five years. We choose the 2002 version as it falls within our sample period. The results are similar if we use the 1997 version instead. As a result, there are 122 industries in total, with manufacturing sector accounting for 73. We obtain a balanced panel of 139,210 observations with 13,921 industry pairs for each year during 1998-2007.

Our dataset excludes horizontal and vertical mergers to avoid other confounding channels. Specifically, we delete horizontal mergers, in which are the acquirers and targets belong to the same industry, and vertical mergers, in which the acquirer and target's industries are vertically related, i.e., one provides more than 5% of the total inputs of the other.[16] We also delete mergers related with the finance industry as they might have very different motivations from other industries. The remaining M&As are called conglomerate mergers. During 1998-2007 in China, 12% mergers are horizontal; 33% occur between vertically related industry; and the rest 55% are conglomerate

[16] This approach is widely used in the literature (e.g., Fan and Lang (2000)). When the cutoff is set to 1%, our results are consistent.

mergers.

We follow Boehm et al. (2022) to define and compute input similarity using the intermediate input matrix in the IO table. Specifically, input similarity between industry i and j is defined as

$$IS_{ij} = \sum_{k} ss_{ki} ss_{kj}, \tag{1}$$

where $ss_{ki} = \frac{X_{ki}}{\sum_h X_{hi}}$, with X_{hi} denoting the value of output from industry h used in the production of industry i. The input share, ss_{ki}, measures the importance of input k among all inputs of i. Evidently, IS_{ij} is larger when industry i and j share more similar input structures.

3 Empirical Design and Results

3.1 Estimating the Effect of Input Similarity on M&As

We first investigate whether input similarity between industries is related to merger likelihood and frequency between industries. Figure 1 provides graphical evidence that industry pairs with a higher input similarity are more likely to merge. To formally test this positive relationship, we estimate the following specification:

$$MA_{ijt} = \beta \cdot IS_{ij} + \alpha_{it} + \alpha_{jt} + \epsilon_{ijt}, \tag{2}$$

where MA_{ijt} denotes M&As between industries i and j in year t. We use two measures of MA_{ijt}. The first is a dummy variable that indicates whether a completed merger occurred between industries i and j; and the second is the inverse hyperbolic sine of the number of completed mergers between industries i and j, that is, $logN_{ijt} \equiv ln(z_{ijt} + \sqrt{z_{ijt}^2 + 1})$, where z_{ijt} is the number of completed mergers. IS_{ij}, is the regressor of interest, defined as the input similarity between industries i in equation (1). α_{it} and α_{jt} are the acquirer and target industry-year fixed effects, which account for all time-variant characteristics at the industry level, such as business cycles and industrial technology shocks, which can drive industry merger waves (Harford, 2005). The error term is clustered at industry-pair level.

The baseline results are shown in Table 1, which confirm a positive correlation between input similarity and mergers. First, we only control for the acquirer and target's industry-year fixed effects in Column (1). The estimated $\hat{\beta}$ is significantly positive, thereby implying that, after taking into account individual industry's factors that could drive mergers (e.g., industry concentration), firms from different industries still tend to merge with each other when they have similar input structures because input similarity helps the firms to realize merger synergies. For example, when acquirers and targets share common buyers, mergers can help to internalize demand complementarities across buyers. However, output similarity between acquirers and targets may also bring merger synergies (e.g., Dhingra (2013)), for example, gaining market power by acquiring competitors with similar outputs. To account for merger incentives caused by output similarity, we also compute output similarity for each industry pair, which is analogous to the input similarity measure. Define $bs_{ik} = \frac{X_{ik}}{\sum_h X_{ih}}$ as the buyer share of industry h among all buyers of i, with X_{ih} denoting the value of product in industry i that is bought and used in the production of industry h. The larger the bs_{ik}, the more important the industry k as a buyer of the product of industry i. The output similarity between industries i and j can be analogously calculated as $OS_{ij} = \sum_k bs_{ik}bs_{jk}$. The higher the OS_{ij}, the higher the output similarity between industries i and j. We then further control for the output similarity measure in the regression, with result presented in Column (2). The coefficient on OS_{ij} is positively significant, implying that output similarity can also cause mergers. More importantly, our key estimate for input similarity remains positive and significant, indicating that concern regarding the demand side has no effect on our finding. Thus, we have confirmed the effect of input similarity on the likelihood of mergers across industries. The impact is also economically significant. Our estimate based on Column (2) indicates that a one standard deviation increase in IS_{ij} will raise the probability of having mergers by 0.21 percentage points. This is about 30% higher than the average occurrence rate of mergers across industry pairs (0.72 percentage points), indicating that input similarity has a non-trivial impact on mergers.

In Columns (3)-(4) we examine the effects on the number of mergers, using the inverse hyperbolic sine of the total number of mergers, $logN_{ijt}$.[17] It is clear that the key estimate remains positive and statistically significant. That is, there are more merger deals between industries with higher input

[17]Results are consistent if we use $log(1 + N)$ instead.

similarity.

<Insert Table 1 Here>

3.2 Causality Identification

The previous section demonstrates that industries with similar input structures have a higher incidence of merger and a higher number of mergers. Although we have controlled for a wide range of industry-level time-varying factors influencing industry merger waves, through the acquirer- and target-industry-year fixed effects, the impact of input similarity on mergers could still be influenced by other confounding factors. For example, if firms with similar inputs cluster together due to agglomeration forces, a common location shock may induce more mergers between them.

We now use an empirical design to overcome the above empirical challenge. Specifically, we exploit the abrupt and drastic import tariff reductions specific to an industry pair's common inputs, as a result of China's WTO accession for identification To fulfill the entry requirement of the WTO, China reduced the tariff rates on a wide range of intermediate inputs in a way that has been treated as close to exogenous in the literature (Brandt et al., 2017). The trade literature demonstrates that industries with higher input tariff reductions benefit more from such a trade liberalization as they can use a larger quantity, a broader variety, and a higher quality of these inputs (Amiti and Konings, 2007; Goldberg et al., 2010; Topalova and Khandelwal, 2011; Bas and Strauss-Kahn, 2015; Fan et al., 2015; Fieler et al., 2018). We can therefore perform a difference-in-differences empirical study based on the policy-induced changes in input similarity across industry pairs. The treatment group includes industry pairs that have a higher ex-ante level of common input usage and also have a substantial reduction in input tariffs. As a result, they enjoyed a larger increase in the input similarity due to China's WTO entry, a fact we confirmed using the change in China's Input-Output Table from 2002 to 2007 and shown in appendix table A3. The remaining industry pairs, which witness a lower increase in the common input usage, constitute the control group. As a result, we can compare the change in the merger proclivity for these two groups of industry pairs, before and after China's WTO entry.

Specifically, we define the shocks to the common inputs between each pair of industries as

$$Shock\text{-}IS_{ijt} = \sum_k shock_{kt} ss_{ki} ss_{kj},$$

where $shock_{kt}$ represents the exogenous shock caused by China's WTO accession to input industry k in year t. To construct the tariff shock, $shock_{kt}$, we first use China's initial tariff level on each industry in 2001 (before WTO accession) to measure the intensity of the tariff reduction in that industry, denoted as $\tau_{k,2001}$ for industry k. This is inspired by the work of (Liu et al., 2019), which shows that the import tariffs across almost all industries were reduced to low levels after 2002 and as a result, the variation of the tariff reductions is primarily in line with the variation in tariff levels in 2001. We then interact the initial tariff $\tau_{k,2001}$ with the dummy for WTO entry to measure the tariff shock, denoting the interaction term as $tariff_{kt} \equiv \tau_{k,2001} \times Post_t$, where $\tau_{k,2001}$ is the log of initial import tariff level of industry k in year 2001 and $Post_t$ is a dummy for the years after 2001. Finally, we use $Tariff\text{-}IS_{ijt} = \sum_k tariff_{kt} ss_{ki} ss_{kj}$ to represent the input tariff shocks to industry pairs with similar inputs. Given the predetermined level of IS_{ij}, industry pairs with a higher $Tariff\text{-}IS_{ijt}$ tend to have better access to inputs in the post-WTO period, as their common inputs face larger import tariff reductions.

To study how the tariff shocks interact with firms' input mix in shaping merger activities, we estimate the following specification:

$$MA_{ijt} = \gamma \cdot Tariff\text{-}IS_{ijt} + \alpha_{ij} + \alpha_{it} + \alpha_{jt} + \epsilon_{ijt},$$

where α_{ij} is the industry-pair fixed effect and other variables have been defined earlier. Note that as we now rely on the time-varying shocks at industry-pair level for identification, we are able to include the industry-pair fixed effect in addition to the acquire-year and target-year fixed effects. The industry-pair fixed effect controls for all unobserved time-invariant factors at the industry-pair level, such as the co-location of input-similar industries. These rich fixed effects greatly alleviate concerns on unobserved confounding factors.[18]

[18] Using IS_{ij} instead of the more flexible industry-pair fixed effects generates consistent results.

Table 2 presents the results and lends support to the causal impact of input similarity. Column (1) shows that, when the common inputs of two industries face larger import tariff reductions, M&As between the two industries are more likely, especially for industries with higher input similarity. We further check whether this causal effect is robust to the concern associated with output similarity, as China's WTO accession also brought about tariff shocks to the industry-pair's common buyers. We construct $Tariff\text{-}MS_{ijt} = \sum_k tariff_{kt} bs_{ik} bs_{jk}$ analogously to the tariff shocks of common inputs, and add to our regression. Column (2) of Table 2 clearly shows that the coefficient of our interest is unaffected.

<Insert Table 2 Here>

Another confounding factor associated with the tariff reduction is the contemporaneous trade policy uncertainty reduction faced by Chinese exports in the US market following China's entry into the WTO (Pierce and Schott, 2016; Handley and Limão, 2017; Liu and Ma, 2020).

Before China was granted with the Permanent Normal Trade Relations (PNTR) upon its accession into WTO, the US import tariffs on Chinese exports may jump back to the so called "column 2" tariffs under the Smoot-Hawley Tariff Act of 1930, depending on the annual review by the US Congress and President. These tariff rates are much higher than the NTR rates, which are offered for members of the WTO by the US. Though the actual tariff rates stayed at the NTR level for China, the threat of rebounding back to column 2 tariffs generated substantial uncertainties for Chinese firms. These uncertainties were resolved after China joined WTO and was granted the PNTR. The higher the gap between the column 2 tariff and the actual tariff, the higher the uncertainty is. Because the actual tariff levels are low, the variation in reduction of uncertainty mainly comes from the initial column 2 tariffs. In line with this literature, we use the column 2 tariffs that were pre-determined long before China's WTO negotiation to measure the intensity of the shock. Consistent with the tariff shocks, we measure the industry-level uncertainty shock as $uncertainty_{kt} = col2_k \times Post_t$, and then calculate shocks to industry-pairs with similar inputs and outputs as $Uncertainty\text{-}IS_{ijt} = \sum_k uncertainty_{kt} ss_{ki} ss_{kj}$ and $Uncertainty\text{-}OS_{ijt} = \sum_k uncertainty_{kt} bs_{ik} bs_{jk}$. Results reported in Column (3) show that our finding is not driven by the uncertainty shock.

We also examine the causal impact of input similarity with an alternative measure of mergers, that is, the inverse hyperbolic sine of the total number of mergers deals $logN_{ijt}$, and report the results in Columns (4)-(6). We consistently find that input similarity has a significant and positive causal impact on mergers.

3.3 Robustness Checks

We now conduct a series of checks to see if our finding is robust or not.

3.3.1 Parallel Pre-trends

In the above subsection, we conduct a difference-in-differences empirical design to exploit the exogenous variations in the changes in common input usage and uncover its causal effect on mergers. One critical assumption for this identification is that without the resultant change in input tariffs due to China's WTO entry, there would be no differential changes in the merger activities across different industry pairs. While this assumption is not testable, we can provide corroborative evidence by examining if the treated and control industry pairs have common pre-trends before the WTO entry. Specifically, we replace the $Post_t$ dummy in $Tariff\text{-}IS_{ijt}$ with a vector of year dummies, and run the following flexible specification

$$MA_{ijt} = \sum_{t=1999}^{2007} \gamma_t \cdot year_t \times IS\_T01_{ij} + \alpha_{ij} + \alpha_{it} + \alpha_{jt} + \epsilon_{ijt},$$

where $IS\_T01_{ij} = \sum_k \tau_{k,2001} ss_{ki} ss_{kj}$ is the intensity of tariff reduction on common inputs of industries i and j. The time-specific variable for the year of 1998 is the omitted baseline.

The results are reported in Column (1) of Table 3, with merger indicator as the dependent variable. The coefficients for years before the WTO entry are insignificant and close to zero, indicating no differential trends in the merger probability between the treated and control industry pairs before the large tariff shocks occurred. We note that the effects do not show up immediately in the first year after China's WTO entry, i.e., year of 2002, and the effects are quite persistent starting from the second year, consistent with a causal impact brought about by the tariff reductions.

<Insert Table 3 Here>

3.3.2 Vertical Integration

Two industries may be vertically related. Vertical mergers have different motives from conglomerate mergers with common inputs. Our paper focuses on the latter and in our baseline sample, we have dropped all vertically related industry pairs with input share $ss_{ij} > 5\%$ to avoid the confounding effect caused by vertical M&As. To be more conservative, we also try to delete vertically related industry pairs with $ss_{ij} > 1\%$ to check the robustness. The results in Column (2) demonstrate that our conclusion is not driven by vertical mergers.

3.3.3 Broader Classification of Horizontal M&As

Horizontal mergers involve firms from the same industry and thus, by definition, they use common inputs. As our focus is on mergers by firms from different industries (i.e., conglomerate mergers), we exclude all horizontal mergers from our baseline sample, in which industries are classified according to the 2002 IO Table, with 122 industries in total. China publishes an IO table with 43 aggregate sectors. For example, the aggregate sector of textiles includes IO industry of cotton textiles, woolen textiles, and other types of textiles, which may be similar or related in other aspects. Therefore, some conglomerate mergers in our baseline sample can be considered as horizontal mergers under the 43-sector IO Table. To exclude those more broadly defined horizontal mergers, we further delete industry pairs that belong to the same sector under the 43-sector IO Table. The results in Column (3) are based on this new sample and demonstrate the robustness of our finding.

3.3.4 Alternative Measure of Industry Similarity

In addition to the measure of input similarity we adopt in equation (1), there exists another commonly used measure, which is the cosine similarity. The cosine input similarity is defined as $CIS_{ij} = \frac{\sum_k ss_{ki}ss_{kj}}{\sqrt{(\sum_k ss_{ki})^2(\sum_k ss_{kj})^2}}$. Correspondingly, we can define the tariff shock on common inputs as $Shock\text{-}CIS_{ijt} = \frac{\sum_k shock_{kt}ss_{ki}ss_{kj}}{\sqrt{(\sum_k ss_{ki})^2(\sum_k ss_{kj})^2}}$. We can also define output similarity and the corresponding shocks in the same way. Results using these alternative measures are reported in Column (4). The estimate remains positive and significant.

3.3.5 Robustness based on Number of Merger Deals

The above robustness checks are performed based on merger likelihood. We also conduct the same robustness tests for the number of merger deals and report the results in Columns (5)-(8). The results are consistent.

3.3.6 Summary

In summary, we conclude that the effects of common input on merger activities are positive, statistically significant, and likely causal.

3.4 Mechanism Tests

In this subsection, we demonstrate that input specificity is the key element of firms' input capability that motivates conglomerate mergers. A firm's core competencies in general and input capability in particular are resources that are difficult to obtain outside of the firm's boundaries. Inputs can be divided as specific and nonspecific. Compared with specific inputs, nonspecific inputs are in general more substitutable and used by more industries. Expertise in using nonspecific inputs is more likely to be common knowledge that can be exchanged outside the firm's boundary, making it difficult to constitute the firm's core competency. Nonspecific inputs are thus less likely to be important in determining firms' strategies and performances. This broad concept has its origins in classic theory on the boundaries of the firm and has been applied in a variety of fields, including Nunn (2007) and Barrot and Sauvagnat (2016). Inspired by this literature, we anticipate that the merger synergies from common inputs are stronger for more differentiated or knowledge intensive inputs, i.e., specific inputs. We now put this prediction to the empirical tests.

To test our prediction, we construct three measures of input specificity. They are the Rauch (1999) classification of goods traded in international markets, R&D intensity the input industry, and patenting intensity of the input industry. Each measure of input specificity separates inputs to two groups and we examine the two groups' differential effects of tariff reductions on mergers between industry pairs with common inputs. First of all, we check and find that the cross-sectional variations in import tariff reductions do not systematically vary in each of our measures of input specificity in a manner that could drive the results, which are presented in appendix table A5.

3.4.1 Differentiated Inputs

Making full use of differentiated inputs, as opposed to homogeneous ones, is more likely to necessitate know-hows and form firms' core competencies. Expertise in handling these differentiated inputs is more valuable and transferable to production in other industries with similar inputs. As a result, we first examine whether tariff shocks to differentiated common inputs are more stronger in determining M&As than those to homogeneous common inputs.

We begin by constructing a measure of the level of differentiation for each input industry. Specifically, Rauch (1999) classifies products as (i) homogeneous, (ii) reference-priced, or (iii) differentiated in nature. The product differentiation of industry k is defined as the share of the constituent HS product codes that is classified as differentiated (i.e., neither homogeneous nor reference-priced) in the composition of the industry, which we denote as $shDF_k$.[19] In our context, the Rauch index can also be interpreted as input contractibility in the sense of Nunn (2007), as it is inherently more difficult to specify and enforce the terms of contractual agreements for such inputs. We can interpret firms' core competencies to include skills in dealing with input suppliers that may require relation-specific investment.

To study how the effect of tariff reductions on mergers depending on the types of common inputs, we calculate the tariff shock on differentiated common inputs as

$$shDF\text{-}Tariff\text{-}IS_{ijt} = \sum_k shDF_k * tariff_{kt} * ss_{ki} * ss_{kj},$$

where $tariff_{kt} = \tau_{k,2001} \times Post_t$, as defined previously. Evidently, given the same input shares ss_{ki} and ss_{kj}, industry pairs that have more differentiated common inputs receiving larger tariff shocks tend to have a higher $shDF\text{-}Tariff\text{-}IS_{ijt}$. With this new measure, we estimate the following

[19] To match the classification of differentiated products from Rauch (1999) to Chinese IO industry, we first map the four-digit SITC with six-digit HS using the correspondence table from WITS, and then map the six-digit HS with Chinese four-digit CIC using correspondence Table from Professor Yifan Zhang, and ultimately match CIC to IO using definition of IO tables. Note that the differentiated products are defined according to SITC, and therefore non-traded products are not included.

specification:

$$MA_{ijt} = \gamma_1 \cdot Tariff\text{-}IS_{ijt} + \gamma_2 \cdot shDF\text{-}Tariff\text{-}IS_{ijt} + \alpha_{ij} + \alpha_{it} + \alpha_{jt} + \epsilon_{ijt}. \quad (3)$$

A positive $\hat{\gamma_2}$ means that the merger incentive increases if firms have more differentiated common inputs with the same level of tariff reduction shocks.

Results are reported in Columns (1) and (4) of Table 4. Evidently, the effects of tariff reductions on merger activities are significantly more pronounced when the common inputs have higher degrees of differentiation.

3.4.2 Innovation-intensive Industry

If production of a firm's inputs are innovation intensive, the firm is likely to have core competencies in using those inputs because the knowledge of those inputs is hard to be acquired by other firms. In fact, Barrot and Sauvagnat (2016) use innovation intensity to proxy for the input specificity. We expect that the effect of input capability and similarity on M&As should manifest in industry pairs that share similar innovation-intensive inputs.

Specifically, we use the average share of R&D expenses over sales, denoted as $shRD_k$, to measure R&D intensity for industry k.[20] Analogously, we construct $shRD\text{-}Tariff\text{-}IS_{ijt} = \sum_k shRD_k * tariff_{kt} * ss_{ki} * ss_{kj}$ to capture tariff shocks on R&D-intensive common inputs. We replace $shDF\text{-}Tariff\text{-}IS_{ijt}$ with $shRD\text{-}Tariff\text{-}IS_{ijt}$, and re-estimate specification (3). Columns (2) and (5) of Table 4 show that the effects are more pronounced when the common inputs are more R&D intensive, subject to given level of import tariff reductions.

R&D expenses are inputs for innovation. We also use the outputs of innovation, i.e., the patents, to measure innovation intensity of an industry. Specifically, we use the average number of patent filings over sales, denoted as $shPT_k$, to measure patent-intensive industries and examine whether the effects are more pronounced when the common inputs are more patent-intensive. Results in Columns (3) and (6) confirm it.

[20] The data is from the Annual Survey of Industrial Firms and do not include agriculture and service industries.

4 Discussions on Alternative Explanations

Our identification utilizes the refined variation of import tariffs on the common inputs between two industries. Other confounders that do not systematically with that shall not violate our finding. In addition, we have also controlled for the tariff and uncertainty shocks at the common buyers to avoid possible perturbation. Nevertheless, we further discuss some alternative explanations can potentially account for our finding that input similarity drives conglomerate mergers.

First comes the bargaining power explanation that firms may merge to increase their bargaining/monopoly power towards suppliers and thus to lower input costs. This incentive has been documented in horizontal mergers (Horn and Wolinsky, 1988). Theoretically, conglomerate mergers between firms with similar inputs can have similar incentives. However, when the import tariffs of inputs reduce, firms have better (alternative) access to inputs, which should lower the merger incentives to build up bargaining power to suppliers. On the contrary, our causal evidence shows that the reductions of input import tariff increase the probability of mergers between firms with similar inputs. Therefore, even if the bargaining power incentive is functioning, it only indicates that our effects are under-estimated.

Second is the economies of scale explanation. When the usage of inputs in production exhibits increasing returns to scale, acquiring firms with similar inputs can reduce the production costs. Pesendorfer (2003) illustrates one example in the paper industry. There are different grades of paper depending on the weight, color and texture. A machine is more efficient the longer it runs and the narrower the range of grades produced, which may be capable after merger when the demand becomes large enough for each grade. Therefore, the economies of scale can also incentivize mergers. However, in this case, we shall not expect significant differences between the usage of specific inputs and non-specific inputs. The more salient effect of tariff reductions of common specific inputs on mergers suggests that the core competencies in input usage is functioning beyond the general economies of scale.

5 Conclusion

We borrow insights from the resource-based theory since Penrose (1955) to show that input capability is an important component of the core competencies of the firm. More specifically, we show that firms are more likely to diversify into industries with similar input structure through M&As to exploit input capability. To identify a causal relationship, we utilize the exogenous import tariff reductions due to China's WTO accession, and find that industry pairs with similar input usage are more likely to have mergers between them if their common inputs experienced higher import tariff reductions. The effects are more pronounced if the common inputs are differentiated, R&D-intensive or patenting-intensive, providing evidence on the input capability channel. Findings from our analyses also suggest a novel channel that trade liberalization can influence the aggregate productivity by affecting mergers and acquisitions and the resultant resource allocations.

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Input Similarity, Core Competencies and M&As

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Abstract

The resource-based view holds that firms diversify to utilize core competencies. We contend that firms' know-how in input usage, or input capability, is a key component of the core competencies and study its implications for mergers and acquisitions. We infer input capability based on the relative input share, and argue that firms can transform their input capability to another industry with similar input usage. We find that firms, when entering new industries through acquisitions, are more likely to target firms with more similar inputs. Utilizing China's WTO entry which lowered import tariffs as a natural experiment, we find that firms are more likely to acquire targets from other industries with larger tariff reductions in their common inputs. Furthermore, the effects are more salient when affected inputs are differentiated or innovation-intensive.

1 Introduction

According to the resource-based view of the firm, firms possess different inalienable and scarce resources or capabilities, that lead to competitive edge and drive business success (Wernerfelt, 1984; Prahalad and Hamel, 1990; Barney, 1991). These resources form the core competencies of a firm and play an important role in shaping the boundary of the firm (Chandler, 1962). More specifically, knowledge about input usage in the incumbent industry, or input capability could be one key element underlying the core competencies of the firm. Since Penrose (1955), the literature

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†*Acknowledgment*: We benefitted from discussions with participants of the 2022 HKU Trade and Development Workshop, and Seminars in IESR, and WHU.

has long recognized that firms can go beyond the limits imposed by the size of a single industry by entering new industries. Firms, therefore, could gain economies of scope by diversifying into industries with common inputs so their "core competencies" can be fruitfully utilized. This idea was provided early by Lemelin (1982) and recently revived by Boehm et al. (2022) to study firm diversifications or internal growth.[1] In this paper, we recall the classic resource-based view of the firm and borrow this insight to understand mergers and acquisitions (M&As).[2] Specifically, we show that the know-how embedded in common input usage is a key determinant for mergers involving parties outside of horizontal or vertical relationships, also known as diversifying deals.[3]

We define and infer a firm's input capability based on the relative input share in its incumbent industry, measured using the input-Output (IO) table, as in Lemelin (1982) and Boehm et al. (2022). The input capability is more likely to be transferable among two industries with a higher degree of common input usage, measured as the similarity score of the input share of these two industries.[4] Using the sample of diversifying or conglomerate mergers, which are mergers excluding horizontal and vertical ones, of Chinese firms from 1998 to 2007 obtained from SDC Platinum, we first look at how the propensity and number of merger deals between any given pair of industries are associated with the degree of common input usage between them. We find a positive and significant correlation between input similarity and M&As. This pattern is evident from a bin-scatter plot where we plot the input similarity of industry pairs into twenty bins, against the pair-wise merger propensities, as shown in Figure 1. We also verify such a relationship in OLS regressions further controlling for the industry-by-year fixed effects of both the acquirer and target industries.[5] The

[1] Lemelin (1982) shows, in a correlational sense, that firms are more likely to operate in different industries when the industries share similar input usage. Boehm et al. (2022) provide causal evidence that Indian plants are more likely to produce goods in a new industry with similar inputs to incumbent goods, using the de-reservation of input industries as a natural experiment.

[2] According to Chen et al. (2022), the combined Google Scholar citation count for Wernerfelt (1984), Prahalad and Hamel (1990), and Barney (1991) is over 150,000, and the resource-based view of the firm is a hugely influential literature that forms a core part of MBA and executive education syllabi, and thus is salient to many decision makers on M&As.

[3] Diversifying deals account for a significant share in M&As. Taking China for example, in our sample period, 1998-2007, 56% M&As are diversifying deals. Similar case is found in the US, where the diversifying deals account for 47% of all M&As during 1978-2019 (Jia and Sun, 2022).

[4] More specifically, for each industry, we know its cost share (i.e., input usage out of total input usage) of any input industry. The input usage structure of a given industry can then be represented as a vector of the industry's cost share. The similarity or inner product of any two industry's cost share vector can therefore be used to measure how similar two industries are in terms of their input usage structure.

[5] Directly controlling for the acquirer industry by year, and target industry by year fixed effects allows us to tease out time-varying changes common to a given industry. For example, industries could be facing disparate situations

economic magnitude is substantial, a one standard deviaion increase in input similarity will raise the propensity of merger deals by about 30% of the average mean. We also directly control for the output similarity of the two industries and find the inference remains unchanged.

However, the positive correlation we uncovered may not be necessarily causal. Industry pairs with a higher level of common input usage could also be more similar in various other dimensions such as technology, human capital profiles, and so on, which have been shown to facilitate synergistic gains and merger activities in general (Rhodes-Kropf and Robinson, 2008) and thus, the result could be subject to omitted-variable bias.[6] Indeed, the existing evidence in the M&A literature on how the similarity between certain firm characteristics is associated with higher merger likelihood is mainly correlational and faces exactly the same empirical challenge.[7]

Our work advances the literature by providing causal evidence that overcomes the aforementioned empirical challenge. To accomplish this, we use China's WTO accession as a natural experiment. As a result of China fulfilling the entry requirement of WTO, the tariff rates for a wide range of intermediate input industries were greatly reduced in a way that has been treated as close to exogenous in the literature (Brandt et al., 2017). Economic theory and empirical evidence show that industries with more tariff reductions on their inputs use a greater quantity, a broader variety, and a higher quality of these inputs.[8] As a result, in the same vein as Boehm et al. (2022), we can make use of the tariff reductions brought about by the WTO entry to generate exogenous variations in input similarity across industry pairs and conduct a difference-in-differences empirical analysis. The treatment group includes industry pairs that have a higher ex-ante level of common input usage and also have a substantial reduction in input tariffs. As a result, they enjoyed a larger increase in the input similarity due to China's WTO entry.[9] The remaining industry pairs, which witness a lower increase in the common input usage, constitute the control group. As a result, we

in the competitive environment or export opportunities due to WTO entry.

[6]For example, due to clustering, industries with similar inputs could be located in nearby regions, thus there could be common regional shocks that correlate with the merger activities. Industries with similar inputs could also have similar labor skill profiles, thus nationwide changes in the structure of the labor force such as the college enrollment expansion started in 1999 could also have an effect.

[7]The growing list of papers includes product similarity (Hoberg and Phillips, 2010), technology overlap (Bena and Li, 2014), human capital relatedness (Lee et al., 2018), and cultural similarity (Bereskin et al., 2018).

[8]See, for example, Amiti and Konings (2007); Goldberg et al. (2010); Topalova and Khandelwal (2011); Bas and Strauss-Kahn (2015); Fan et al. (2015); Fieler et al. (2018).

[9]We confirm that this is indeed the case, using the change in China's Input-Output Table from 2002 to 2007 and results are presented in appendix table A3.

can compare the change in the merger proclivity for these two groups of industry pairs, before and after China's WTO entry. The findings support our hypothesis: industry pairs with more ex-ante similar inputs and higher tariff reductions as a result of WTO accession are significantly more likely to conduct M&A among themselves.

An important identifying assumption behind our difference-in-differences empirical design is that, had China not joined the WTO in 2001, there would be no differential trends in merger activities between these two groups of industry pairs. While this assumption is not testable, we provide corroborative evidence by conducting the dynamic analysis, and find that our treatment and control groups have similar trends in merger dynamics before the 2001 WTO entry. Our results are also robust to controlling for the import tariff shocks for the common outputs, as well as the trade policy uncertainty shocks from the US. We further conduct a set of robustness checks including perturbing the threshold in dropping industry pairs with potential vertical relationship, defining diversifying deals using a more aggregated industry classification, and using the cosine similarity measure to capture input similarity. Our findings are invariant to these tests.

We further exploit the characteristics across inputs to shed light on the mechanism that it is the *core competencies* in input usages that drives our findings. Core competencies rely on resources that are costly to acquire outside the firm (Penrose, 1955; Chandler, 1962), therefore, in terms of input usage, they should matter more for specific inputs (Nunn, 2007; Barrot and Sauvagnat, 2016).[10] We use three alternative measures of input specificity. The first one is the Rauch (1999) classification of differentiated vs. homogeneous goods. Second, we use the industry average R&D expenditure shares to capture the know-how imbedded in each input. Lastly, we use the industry average patent intensity, measured by the total patent counts over total sales.[11] We find that the causal effects of input similarity on merger activities are significantly stronger when the common inputs are more specific, consistent with our contention that capabilities in input usages are behind firms' core competencies.

Our work contributes primarily to the M&A literature. M&As are among the most important

[10]Non-specific inputs are in general more substitutable and used by more industries. Expertise in using them tends to be common knowledge that is exchangeable outside the firm's boundary, making it less likely to constitute the firm's core competencies.

[11]We also confirm that the degree of tariff reductions do not systematically vary with our measures of input specificity, so that we capture effects from different input specificity conditional on the level of tariff reductions.

types of corporate investment activities and bear critical implications for the efficient reallocation of resources in the economy.[12] More specifically, we contribute to a growing literature that understand the determinants behind deals outside of horizontal or vertical relationships, also known as diversifying or conglomerate deals. Existing literature demonstrates that determinants of such merger deals include asset complementarity due to product similarity (Hoberg and Phillips, 2010), technology overlap (Bena and Li, 2014), human capital relatedness (Lee et al., 2018), and cultural similarity (Bereskin et al., 2018) between the acquirers and targets. While these works mainly show correlational evidence, we are able to provide causal evidence based on a difference-in-differences empirical design that exploits China's WTO entry as a quasi natural experiment.

Our work is particularly relevant to the literature that uncovers merger motives related to the efficiency gains, or cost reductions.[13] The merger motive that we argue fits into these studies on several fronts. First, Horn and Wolinsky (1988) show that firms benefit from a merger by increasing their bargaining power toward suppliers to reduce the input price. In studying mergers in the paper industry, Pesendorfer (2003) finds a higher efficiency gain in cost and conjectures that one of the cost savings induced by mergers could be the more efficient allocation of inputs. In studying the lodging industry, Kalnins et al. (2017) show that merging firms could enjoy a lower marginal cost due to the increased size of common inputs, or the increased capacity utilization when their outputs face stochastic but independent demand. Our finding that input similarity increases mergers is in line with these motives as common input usage allows the merged entities to better exploit those benefit. Second, we argue that firms' know-how of their input usage could be an important element of core competencies that can be transferred to firms in distinct industries and lead to efficiency gains. Bloom et al. (2012) show that US firms can transplant their superior usage of IT to their acquired establishments in UK. Apparently, firms' capabilities in the usage of production inputs do not have to be confined to IT and we show that this know-how transplant is especially the case for specific inputs that are differentiated, or knowledge-intensive.

Our work also contributes to the strategy and management literature on the resource-based

[12] Evidence shows that M&As affect employment (Geurts and Van Biesebroeck, 2019), improve plant-level productivity (McGuckin and Nguyen, 1995; Maksimovic and Phillips, 2001; Schoar, 2002; Harris et al., 2005) and profitability (Braguinsky et al., 2015), and aid the diffusion of new technologies (Jovanovic and Rousseau, 2008).

[13] Another notable source of efficiency gains or synergies is the scale economies in production, as in the case of brewing industry (Grieco et al., 2018), and lodging industry (Kalnins et al., 2017).

theory of the firm (Wernerfelt, 1984; Prahalad and Hamel, 1990; Barney, 1991). As pointed out by Chen et al. (2022), this is a hugely influential literature that forms a core part of MBA and executive education, and thus salient to decision makers of M&A. Our paper is closely related to Boehm et al. (2022), who study how input similarity can explain the new product introductions at the plant level. While both papers share a common theme, there are significant differences. First, we explore and find that specific inputs matter much more in the effect of common input capabilities. Second, in our setting of M&As, the acquirer can not only transfer its core capabilities in input usage from its industry to the target, but also can receive such a transfer from the target firm. This two-way feedback effect is absent in the case of a firm's organic growth such as Boehm et al. (2022): when a plant offers a new product, it could only rely on its own capabilities. At the same time, our paper is also consistent with a broader literature that emphasizes asset complementarity and synergy creation in M&As (Rhodes-Kropf and Robinson, 2008).

Lastly, our work contributes to the literature of international trade and trade policies [14] More specifically, a strand of the literature documents substantial productivity and growth enhancing role of trade liberalization in intermediate inputs, as imported inputs have been found to improve firm productivity, increase product scope and quality, promote innovation, and facilitate firms' exports.[15] In particular, we join a small but growing works such as Breinlich (2008) and Liu et al. (2019) that study how trade policies could have an aggregate productivity effect, by promoting resource allocations through mergers and acquisitions activities. While these two papers examine the impact on horizontal and vertical industries, respectively, our paper complements them and studies mergers among different industries (i.e., conglomerate mergers) that share similar inputs.

[14]The trade literature currently adopts a narrower scope of 'core competency' and uses it to refer to the core product that a firm can produce with least marginal cost. This assumption has been widely used in models of multiproduct firms such as Eckel and Neary (2009), Mayer et al. (2014), and Arkolakis et al. (2021). A large empirical literature also differentiates between core products and peripheral products, for example, Bernard et al. (2011), Ma et al. (2014), and Manova and Yu (2017). However, as pointed out by Ding (2023), such a modelling approach precludes cost or input complementarity from multi-industry operations and can be restrictive.

[15]See, for example, Amiti and Konings (2007); Goldberg et al. (2010); Topalova and Khandelwal (2011); Bas and Strauss-Kahn (2015); Fan et al. (2015); Feng et al. (2016); Liu and Qiu (2016); Fieler et al. (2018).

2 Data and Variables

The merger data comes from Thomson Reuters SDC Platinum (SDC). This database contains deal-level data from worldwide M&A transactions involving at least 5% ownership of the target and a transaction value of one million US dollars or more, or where the transaction value is unknown. The database contains information of targets and acquirers such as firm name, country, industry, parent firm, primary business, and key financial characteristics. It also includes information of each M&A transaction such as the announcement time, completion status, time to completion, value of transaction, and transaction share. Our research focuses on domestic M&As in China, so we extract all transactions from the SDC database that have both the acquirer and target countries listed as China (excluding Hong Kong, Macao, and Taiwan for the sake of pure "domestic firms" by convention). To be consistent with the similarity measures, the industry is defined at the Chinese Input-Output (IO) industry level. As a result, each firm is assigned to an IO industry based on its primary industry classification at the SIC four-digit level designated by SDC.

Our dataset contains all *completed* Chinese domestic mergers from 1998 to 2007. We choose 2007 as the end year of the sample period to avoid the confounding effects of the global financial crisis. We use the Chinese IO Table in 2002 to classify industries. The IO table is published by the National Bureau of Statistics of China every five years. We choose the 2002 version as it falls within our sample period. The results are similar if we use the 1997 version instead. As a result, there are 122 industries in total, with manufacturing sector accounting for 73. We obtain a balanced panel of 139,210 observations with 13,921 industry pairs for each year during 1998-2007.

Our dataset excludes horizontal and vertical mergers to avoid other confounding channels. Specifically, we delete horizontal mergers, in which are the acquirers and targets belong to the same industry, and vertical mergers, in which the acquirer and target's industries are vertically related, i.e., one provides more than 5% of the total inputs of the other.[16] We also delete mergers related with the finance industry as they might have very different motivations from other industries. The remaining M&As are called conglomerate mergers. During 1998-2007 in China, 12% mergers are horizontal; 33% occur between vertically related industry; and the rest 55% are conglomerate

[16]This approach is widely used in the literature (e.g., Fan and Lang (2000)). When the cutoff is set to 1%, our results are consistent.

mergers.

We follow Boehm et al. (2022) to define and compute input similarity using the intermediate input matrix in the IO table. Specifically, input similarity between industry i and j is defined as

$$IS_{ij} = \sum_k ss_{ki} ss_{kj}, \tag{1}$$

where $ss_{ki} = \frac{X_{ki}}{\sum_h X_{hi}}$, with X_{hi} denoting the value of output from industry h used in the production of industry i. The input share, ss_{ki}, measures the importance of input k among all inputs of i. Evidently, IS_{ij} is larger when industry i and j share more similar input structures.

3 Empirical Design and Results

3.1 Estimating the Effect of Input Similarity on M&As

We first investigate whether input similarity between industries is related to merger likelihood and frequency between industries. Figure 1 provides graphical evidence that industry pairs with a higher input similarity are more likely to merge. To formally test this positive relationship, we estimate the following specification:

$$MA_{ijt} = \beta \cdot IS_{ij} + \alpha_{it} + \alpha_{jt} + \epsilon_{ijt}, \tag{2}$$

where MA_{ijt} denotes M&As between industries i and j in year t. We use two measures of MA_{ijt}. The first is a dummy variable that indicates whether a completed merger occurred between industries i and j; and the second is the inverse hyperbolic sine of the number of completed mergers between industries i and j, that is, $logN_{ijt} \equiv ln(z_{ijt} + \sqrt{z_{ijt}^2 + 1})$, where z_{ijt} is the number of completed mergers. IS_{ij}, is the regressor of interest, defined as the input similarity between industries i in equation (1). α_{it} and α_{jt} are the acquirer and target industry-year fixed effects, which account for all time-variant characteristics at the industry level, such as business cycles and industrial technology shocks, which can drive industry merger waves (Harford, 2005). The error term is clustered at industry-pair level.

The baseline results are shown in Table 1, which confirm a positive correlation between input similarity and mergers. First, we only control for the acquirer and target's industry-year fixed effects in Column (1). The estimated $\hat{\beta}$ is significantly positive, thereby implying that, after taking into account individual industry's factors that could drive mergers (e.g., industry concentration), firms from different industries still tend to merge with each other when they have similar input structures because input similarity helps the firms to realize merger synergies. For example, when acquirers and targets share common buyers, mergers can help to internalize demand complementarities across buyers. However, output similarity between acquirers and targets may also bring merger synergies (e.g., Dhingra (2013)), for example, gaining market power by acquiring competitors with similar outputs. To account for merger incentives caused by output similarity, we also compute output similarity for each industry pair, which is analogous to the input similarity measure. Define $bs_{ik} = \frac{X_{ik}}{\sum_h X_{ih}}$ as the buyer share of industry h among all buyers of i, with X_{ih} denoting the value of product in industry i that is bought and used in the production of industry h. The larger the bs_{ik}, the more important the industry k as a buyer of the product of industry i. The output similarity between industries i and j can be analogously calculated as $OS_{ij} = \sum_k bs_{ik} bs_{jk}$. The higher the OS_{ij}, the higher the output similarity between industries i and j. We then further control for the output similarity measure in the regression, with result presented in Column (2). The coefficient on OS_{ij} is positively significant, implying that output similarity can also cause mergers. More importantly, our key estimate for input similarity remains positive and significant, indicating that concern regarding the demand side has no effect on our finding. Thus, we have confirmed the effect of input similarity on the likelihood of mergers across industries. The impact is also economically significant. Our estimate based on Column (2) indicates that a one standard deviation increase in IS_{ij} will raise the probability of having mergers by 0.21 percentage points. This is about 30% higher than the average occurrence rate of mergers across industry pairs (0.72 percentage points), indicating that input similarity has a non-trivial impact on mergers.

In Columns (3)-(4) we examine the effects on the number of mergers, using the inverse hyperbolic sine of the total number of mergers, $logN_{ijt}$.[17] It is clear that the key estimate remains positive and statistically significant. That is, there are more merger deals between industries with higher input

[17] Results are consistent if we use $log(1 + N)$ instead.

similarity.

<Insert Table 1 Here>

3.2 Causality Identification

The previous section demonstrates that industries with similar input structures have a higher incidence of merger and a higher number of mergers. Although we have controlled for a wide range of industry-level time-varying factors influencing industry merger waves, through the acquirer- and target-industry-year fixed effects, the impact of input similarity on mergers could still be influenced by other confounding factors. For example, if firms with similar inputs cluster together due to agglomeration forces, a common location shock may induce more mergers between them.

We now use an empirical design to overcome the above empirical challenge. Specifically, we exploit the abrupt and drastic import tariff reductions specific to an industry pair's common inputs, as a result of China's WTO accession for identification To fulfill the entry requirement of the WTO, China reduced the tariff rates on a wide range of intermediate inputs in a way that has been treated as close to exogenous in the literature (Brandt et al., 2017). The trade literature demonstrates that industries with higher input tariff reductions benefit more from such a trade liberalization as they can use a larger quantity, a broader variety, and a higher quality of these inputs (Amiti and Konings, 2007; Goldberg et al., 2010; Topalova and Khandelwal, 2011; Bas and Strauss-Kahn, 2015; Fan et al., 2015; Fieler et al., 2018). We can therefore perform a difference-in-differences empirical study based on the policy-induced changes in input similarity across industry pairs. The treatment group includes industry pairs that have a higher ex-ante level of common input usage and also have a substantial reduction in input tariffs. As a result, they enjoyed a larger increase in the input similarity due to China's WTO entry, a fact we confirmed using the change in China's Input-Output Table from 2002 to 2007 and shown in appendix table A3. The remaining industry pairs, which witness a lower increase in the common input usage, constitute the control group. As a result, we can compare the change in the merger proclivity for these two groups of industry pairs, before and after China's WTO entry.

Specifically, we define the shocks to the common inputs between each pair of industries as

$$Shock\text{-}IS_{ijt} = \sum_k shock_{kt} ss_{ki} ss_{kj},$$

where $shock_{kt}$ represents the exogenous shock caused by China's WTO accession to input industry k in year t. To construct the tariff shock, $shock_{kt}$, we first use China's initial tariff level on each industry in 2001 (before WTO accession) to measure the intensity of the tariff reduction in that industry, denoted as $\tau_{k,2001}$ for industry k. This is inspired by the work of (Liu et al., 2019), which shows that the import tariffs across almost all industries were reduced to low levels after 2002 and as a result, the variation of the tariff reductions is primarily in line with the variation in tariff levels in 2001. We then interact the initial tariff $\tau_{k,2001}$ with the dummy for WTO entry to measure the tariff shock, denoting the interaction term as $tariff_{kt} \equiv \tau_{k,2001} \times Post_t$, where $\tau_{k,2001}$ is the log of initial import tariff level of industry k in year 2001 and $Post_t$ is a dummy for the years after 2001. Finally, we use $Tariff\text{-}IS_{ijt} = \sum_k tariff_{kt} ss_{ki} ss_{kj}$ to represent the input tariff shocks to industry pairs with similar inputs. Given the predetermined level of IS_{ij}, industry pairs with a higher $Tariff\text{-}IS_{ijt}$ tend to have better access to inputs in the post-WTO period, as their common inputs face larger import tariff reductions.

To study how the tariff shocks interact with firms' input mix in shaping merger activities, we estimate the following specification:

$$MA_{ijt} = \gamma \cdot Tariff\text{-}IS_{ijt} + \alpha_{ij} + \alpha_{it} + \alpha_{jt} + \epsilon_{ijt},$$

where α_{ij} is the industry-pair fixed effect and other variables have been defined earlier. Note that as we now rely on the time-varying shocks at industry-pair level for identification, we are able to include the industry-pair fixed effect in addition to the acquire-year and target-year fixed effects. The industry-pair fixed effect controls for all unobserved time-invariant factors at the industry-pair level, such as the co-location of input-similar industries. These rich fixed effects greatly alleviate concerns on unobserved confounding factors.[18]

[18]Using IS_{ij} instead of the more flexible industry-pair fixed effects generates consistent results.

Table 2 presents the results and lends support to the causal impact of input similarity. Column (1) shows that, when the common inputs of two industries face larger import tariff reductions, M&As between the two industries are more likely, especially for industries with higher input similarity. We further check whether this causal effect is robust to the concern associated with output similarity, as China's WTO accession also brought about tariff shocks to the industry-pair's common buyers. We construct $Tariff\text{-}MS_{ijt} = \sum_k tariff_{kt} bs_{ik} bs_{jk}$ analogously to the tariff shocks of common inputs, and add to our regression. Column (2) of Table 2 clearly shows that the coefficient of our interest is unaffected.

<Insert Table 2 Here>

Another confounding factor associated with the tariff reduction is the contemporaneous trade policy uncertainty reduction faced by Chinese exports in the US market following China's entry into the WTO (Pierce and Schott, 2016; Handley and Limão, 2017; Liu and Ma, 2020).

Before China was granted with the Permanent Normal Trade Relations (PNTR) upon its accession into WTO, the US import tariffs on Chinese exports may jump back to the so called "column 2" tariffs under the Smoot-Hawley Tariff Act of 1930, depending on the annual review by the US Congress and President. These tariff rates are much higher than the NTR rates, which are offered for members of the WTO by the US. Though the actual tariff rates stayed at the NTR level for China, the threat of rebounding back to column 2 tariffs generated substantial uncertainties for Chinese firms. These uncertainties were resolved after China joined WTO and was granted the PNTR. The higher the gap between the column 2 tariff and the actual tariff, the higher the uncertainty is. Because the actual tariff levels are low, the variation in reduction of uncertainty mainly comes from the initial column 2 tariffs. In line with this literature, we use the column 2 tariffs that were pre-determined long before China's WTO negotiation to measure the intensity of the shock. Consistent with the tariff shocks, we measure the industry-level uncertainty shock as $uncertainty_{kt} = col2_k \times Post_t$, and then calculate shocks to industry-pairs with similar inputs and outputs as $Uncertainty\text{-}IS_{ijt} = \sum_k uncertainty_{kt} ss_{ki} ss_{kj}$ and $Uncertainty\text{-}OS_{ijt} = \sum_k uncertainty_{kt} bs_{ik} bs_{jk}$. Results reported in Column (3) show that our finding is not driven by the uncertainty shock.

We also examine the causal impact of input similarity with an alternative measure of mergers, that is, the inverse hyperbolic sine of the total number of mergers deals $logN_{ijt}$, and report the results in Columns (4)-(6). We consistently find that input similarity has a significant and positive causal impact on mergers.

3.3 Robustness Checks

We now conduct a series of checks to see if our finding is robust or not.

3.3.1 Parallel Pre-trends

In the above subsection, we conduct a difference-in-differences empirical design to exploit the exogenous variations in the changes in common input usage and uncover its causal effect on mergers. One critical assumption for this identification is that without the resultant change in input tariffs due to China's WTO entry, there would be no differential changes in the merger activities across different industry pairs. While this assumption is not testable, we can provide corroborative evidence by examining if the treated and control industry pairs have common pre-trends before the WTO entry. Specifically, we replace the $Post_t$ dummy in $Tariff\text{-}IS_{ijt}$ with a vector of year dummies, and run the following flexible specification

$$MA_{ijt} = \sum_{t=1999}^{2007} \gamma_t \cdot year_t \times IS\_T01_{ij} + \alpha_{ij} + \alpha_{it} + \alpha_{jt} + \epsilon_{ijt},$$

where $IS\_T01_{ij} = \sum_k \tau_{k,2001} ss_{ki} ss_{kj}$ is the intensity of tariff reduction on common inputs of industries i and j. The time-specific variable for the year of 1998 is the omitted baseline.

The results are reported in Column (1) of Table 3, with merger indicator as the dependent variable. The coefficients for years before the WTO entry are insignificant and close to zero, indicating no differential trends in the merger probability between the treated and control industry pairs before the large tariff shocks occurred. We note that the effects do not show up immediately in the first year after China's WTO entry, i.e., year of 2002, and the effects are quite persistent starting from the second year, consistent with a causal impact brought about by the tariff reductions.

<Insert Table 3 Here>

3.3.2 Vertical Integration

Two industries may be vertically related. Vertical mergers have different motives from conglomerate mergers with common inputs. Our paper focuses on the latter and in our baseline sample, we have dropped all vertically related industry pairs with input share $ss_{ij} > 5\%$ to avoid the confounding effect caused by vertical M&As. To be more conservative, we also try to delete vertically related industry pairs with $ss_{ij} > 1\%$ to check the robustness. The results in Column (2) demonstrate that our conclusion is not driven by vertical mergers.

3.3.3 Broader Classification of Horizontal M&As

Horizontal mergers involve firms from the same industry and thus, by definition, they use common inputs. As our focus is on mergers by firms from different industries (i.e., conglomerate mergers), we exclude all horizontal mergers from our baseline sample, in which industries are classified according to the 2002 IO Table, with 122 industries in total. China publishes an IO table with 43 aggregate sectors. For example, the aggregate sector of textiles includes IO industry of cotton textiles, woolen textiles, and other types of textiles, which may be similar or related in other aspects. Therefore, some conglomerate mergers in our baseline sample can be considered as horizontal mergers under the 43-sector IO Table. To exclude those more broadly defined horizontal mergers, we further delete industry pairs that belong to the same sector under the 43-sector IO Table. The results in Column (3) are based on this new sample and demonstrate the robustness of our finding.

3.3.4 Alternative Measure of Industry Similarity

In addition to the measure of input similarity we adopt in equation (1), there exists another commonly used measure, which is the cosine similarity. The cosine input similarity is defined as $CIS_{ij} = \frac{\sum_k ss_{ki} ss_{kj}}{\sqrt{(\sum_k ss_{ki})^2 (\sum_k ss_{kj})^2}}$. Correspondingly, we can define the tariff shock on common inputs as $Shock\text{-}CIS_{ijt} = \frac{\sum_k shock_{kt} ss_{ki} ss_{kj}}{\sqrt{(\sum_k ss_{ki})^2 (\sum_k ss_{kj})^2}}$. We can also define output similarity and the corresponding shocks in the same way. Results using these alternative measures are reported in Column (4). The estimate remains positive and significant.

3.3.5 Robustness based on Number of Merger Deals

The above robustness checks are performed based on merger likelihood. We also conduct the same robustness tests for the number of merger deals and report the results in Columns (5)-(8). The results are consistent.

3.3.6 Summary

In summary, we conclude that the effects of common input on merger activities are positive, statistically significant, and likely causal.

3.4 Mechanism Tests

In this subsection, we demonstrate that input specificity is the key element of firms' input capability that motivates conglomerate mergers. A firm's core competencies in general and input capability in particular are resources that are difficult to obtain outside of the firm's boundaries. Inputs can be divided as specific and nonspecific. Compared with specific inputs, nonspecific inputs are in general more substitutable and used by more industries. Expertise in using nonspecific inputs is more likely to be common knowledge that can be exchanged outside the firm's boundary, making it difficult to constitute the firm's core competency. Nonspecific inputs are thus less likely to be important in determining firms' strategies and performances. This broad concept has its origins in classic theory on the boundaries of the firm and has been applied in a variety of fields, including Nunn (2007) and Barrot and Sauvagnat (2016). Inspired by this literature, we anticipate that the merger synergies from common inputs are stronger for more differentiated or knowledge intensive inputs, i.e., specific inputs. We now put this prediction to the empirical tests.

To test our prediction, we construct three measures of input specificity. They are the Rauch (1999) classification of goods traded in international markets, R&D intensity the input industry, and patenting intensity of the input industry. Each measure of input specificity separates inputs to two groups and we examine the two groups' differential effects of tariff reductions on mergers between industry pairs with common inputs. First of all, we check and find that the cross-sectional variations in import tariff reductions do not systematically vary in each of our measures of input specificity in a manner that could drive the results, which are presented in appendix table A5.

3.4.1 Differentiated Inputs

Making full use of differentiated inputs, as opposed to homogeneous ones, is more likely to necessitate know-hows and form firms' core competencies. Expertise in handling these differentiated inputs is more valuable and transferable to production in other industries with similar inputs. As a result, we first examine whether tariff shocks to differentiated common inputs are more stronger in determining M&As than those to homogeneous common inputs.

We begin by constructing a measure of the level of differentiation for each input industry. Specifically, Rauch (1999) classifies products as (i) homogeneous, (ii) reference-priced, or (iii) differentiated in nature. The product differentiation of industry k is defined as the share of the constituent HS product codes that is classified as differentiated (i.e., neither homogeneous nor reference-priced) in the composition of the industry, which we denote as $shDF_k$.[19] In our context, the Rauch index can also be interpreted as input contractibility in the sense of Nunn (2007), as it is inherently more difficult to specify and enforce the terms of contractual agreements for such inputs. We can interpret firms' core competencies to include skills in dealing with input suppliers that may require relation-specific investment.

To study how the effect of tariff reductions on mergers depending on the types of common inputs, we calculate the tariff shock on differentiated common inputs as

$$shDF\text{-}Tariff\text{-}IS_{ijt} = \sum_k shDF_k * tariff_{kt} * ss_{ki} * ss_{kj},$$

where $tariff_{kt} = \tau_{k,2001} \times Post_t$, as defined previously. Evidently, given the same input shares ss_{ki} and ss_{kj}, industry pairs that have more differentiated common inputs receiving larger tariff shocks tend to have a higher $shDF\text{-}Tariff\text{-}IS_{ijt}$. With this new measure, we estimate the following

[19] To match the classification of differentiated products from Rauch (1999) to Chinese IO industry, we first map the four-digit SITC with six-digit HS using the correspondence table from WITS, and then map the six-digit HS with Chinese four-digit CIC using correspondence Table from Professor Yifan Zhang, and ultimately match CIC to IO using definition of IO tables. Note that the differentiated products are defined according to SITC, and therefore non-traded products are not included.

specification:

$$MA_{ijt} = \gamma_1 \cdot Tariff\text{-}IS_{ijt} + \gamma_2 \cdot shDF\ \text{-}Tariff\text{-}IS_{ijt} + \alpha_{ij} + \alpha_{it} + \alpha_{jt} + \epsilon_{ijt}. \tag{3}$$

A positive $\hat{\gamma_2}$ means that the merger incentive increases if firms have more differentiated common inputs with the same level of tariff reduction shocks.

Results are reported in Columns (1) and (4) of Table 4. Evidently, the effects of tariff reductions on merger activities are significantly more pronounced when the common inputs have higher degrees of differentiation.

3.4.2 Innovation-intensive Industry

If production of a firm's inputs are innovation intensive, the firm is likely to have core competencies in using those inputs because the knowledge of those inputs is hard to be acquired by other firms. In fact, Barrot and Sauvagnat (2016) use innovation intensity to proxy for the input specificity. We expect that the effect of input capability and similarity on M&As should manifest in industry pairs that share similar innovation-intensive inputs.

Specifically, we use the average share of R&D expenses over sales, denoted as $shRD_k$, to measure R&D intensity for industry k.[20] Analogously, we construct $shRD\text{-}Tariff\text{-}IS_{ijt} = \sum_k shRD_k * tariff_{kt} * ss_{ki} * ss_{kj}$ to capture tariff shocks on R&D-intensive common inputs. We replace $shDF\text{-}Tariff\text{-}IS_{ijt}$ with $shRD\text{-}Tariff\text{-}IS_{ijt}$, and re-estimate specification (3). Columns (2) and (5) of Table 4 show that the effects are more pronounced when the common inputs are more R&D intensive, subject to given level of import tariff reductions.

R&D expenses are inputs for innovation. We also use the outputs of innovation, i.e., the patents, to measure innovation intensity of an industry. Specifically, we use the average number of patent filings over sales, denoted as $shPT_k$, to measure patent-intensive industries and examine whether the effects are more pronounced when the common inputs are more patent-intensive. Results in Columns (3) and (6) confirm it.

[20]The data is from the Annual Survey of Industrial Firms and do not include agriculture and service industries.

4 Discussions on Alternative Explanations

Our identification utilizes the refined variation of import tariffs on the common inputs between two industries. Other confounders that do not systematically with that shall not violate our finding. In addition, we have also controlled for the tariff and uncertainty shocks at the common buyers to avoid possible perturbation. Nevertheless, we further discuss some alternative explanations can potentially account for our finding that input similarity drives conglomerate mergers.

First comes the bargaining power explanation that firms may merge to increase their bargaining/monopoly power towards suppliers and thus to lower input costs. This incentive has been documented in horizontal mergers (Horn and Wolinsky, 1988). Theoretically, conglomerate mergers between firms with similar inputs can have similar incentives. However, when the import tariffs of inputs reduce, firms have better (alternative) access to inputs, which should lower the merger incentives to build up bargaining power to suppliers. On the contrary, our causal evidence shows that the reductions of input import tariff increase the probability of mergers between firms with similar inputs. Therefore, even if the bargaining power incentive is functioning, it only indicates that our effects are under-estimated.

Second is the economies of scale explanation. When the usage of inputs in production exhibits increasing returns to scale, acquiring firms with similar inputs can reduce the production costs. Pesendorfer (2003) illustrates one example in the paper industry. There are different grades of paper depending on the weight, color and texture. A machine is more efficient the longer it runs and the narrower the range of grades produced, which may be capable after merger when the demand becomes large enough for each grade. Therefore, the economies of scale can also incentivize mergers. However, in this case, we shall not expect significant differences between the usage of specific inputs and non-specific inputs. The more salient effect of tariff reductions of common specific inputs on mergers suggests that the core competencies in input usage is functioning beyond the general economies of scale.

5 Conclusion

We borrow insights from the resource-based theory since Penrose (1955) to show that input capability is an important component of the core competencies of the firm. More specifically, we show that firms are more likely to diversify into industries with similar input structure through M&As to exploit input capability. To identify a causal relationship, we utilize the exogenous import tariff reductions due to China's WTO accession, and find that industry pairs with similar input usage are more likely to have mergers between them if their common inputs experienced higher import tariff reductions. The effects are more pronounced if the common inputs are differentiated, R&D-intensive or patenting-intensive, providing evidence on the input capability channel. Findings from our analyses also suggest a novel channel that trade liberalization can influence the aggregate productivity by affecting mergers and acquisitions and the resultant resource allocations.

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Figures and Tables

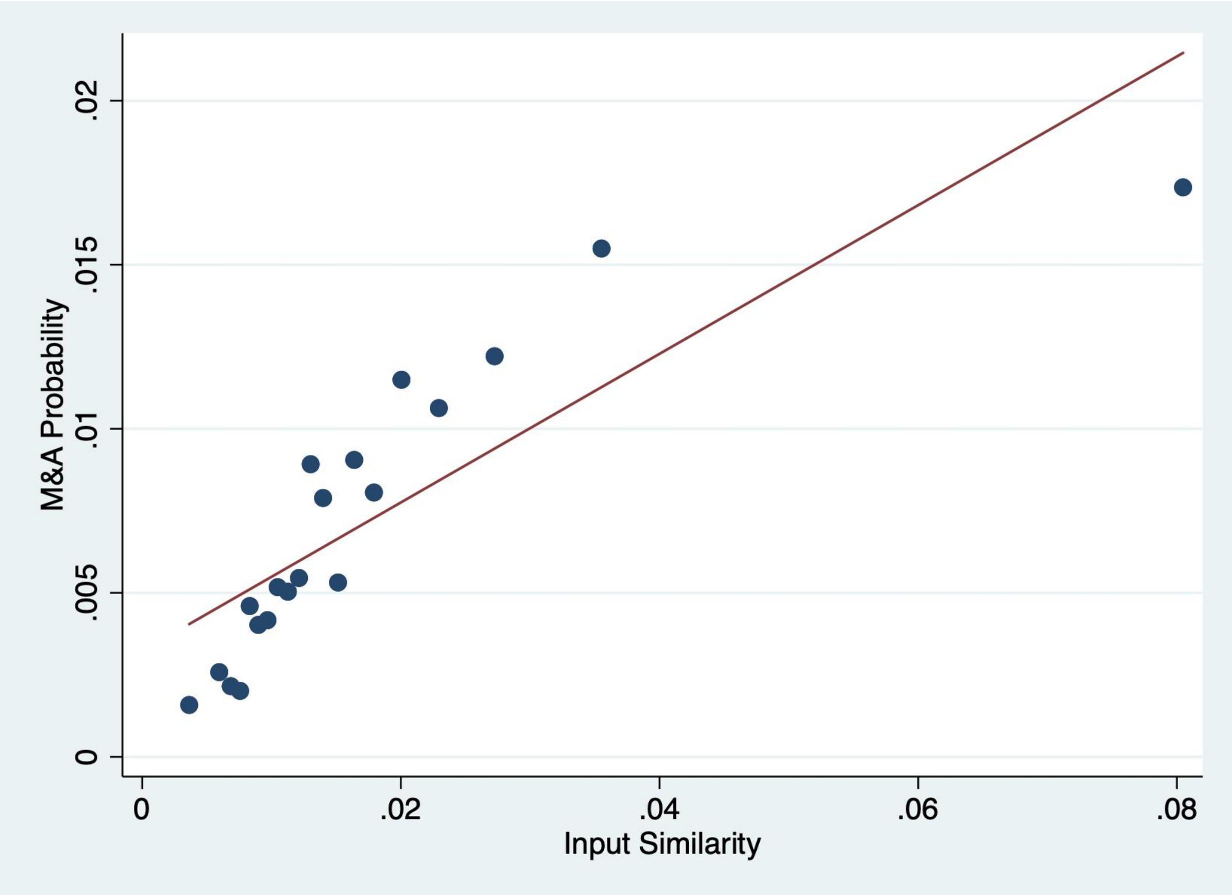

Figure 1 Bin scatter of Input Similarity and Mergers&Acquisitions (M&As) occurrence (20 bins)
Note: The last bin will only bias our estimate downward, therefore our results are robust to them.

Table 1 Baseline Results

	$Dummy_{ijt}$		$LogN_{ijt}$	
	(1)	(2)	(3)	(4)
IS_{ij}	0.1202***	0.1099***	0.1302***	0.1204***
	(0.0183)	(0.0182)	(0.0228)	(0.0230)
OS_{ij}		0.0355***		0.0342***
		(0.0085)		(0.0091)
Fixed Effects		*it, jt*		
N	139,210	139,210	139,210	139,210

Note: $Dummy_{ijt}$ is an indicator on whether industry *i* and *j* have mergers in year *t*; $LogN_{ijt}$ is the inverse hyperbolic sine of the total number of mergers between industry *i* and *j* in year *t;* IS_{ij} and OS_{ij} are the input and buyer similarity of industry-pair *ij*, respectively. We also include the acquirer-year and target-year fixed effects (*it, jt*) to account for all industry level time-variant characteristics. Robust standard errors clustered at industry-pair level. * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table 2 Tariff Shocks and the Causal Effect

	$Dummy_{ijt}$			*$LogN_{ijt}$*		
	(1)	(2)	(3)	(4)	(5)	(6)
$Tairff\text{-}IS_{ijt}$	0.0820***	0.0729***	0.1222***	0.0891***	0.0799***	0.1039***
	(0.0164)	(0.0163)	(0.0395)	(0.0188)	(0.0190)	(0.0362)
$Tairff\text{-}OS_{ijt}$		0.0386**	0.0258		0.0392*	0.0195
		(0.0197)	(0.0369)		(0.0222)	(0.0427)
$Uncertainty\text{-}IS_{ijt}$			-0.0054			-0.0027
			(0.0037)			(0.0038)
$Uncertainty\text{-}OS_{ijt}$			0.0015			0.0021
			(0.0050)			(0.0053)
Fixed Effects	*ij,it, jt*					
N	139,210	139,210	139,210	139,210	139,210	139,210

Note: *$Tairff\text{-}IS_{ijt}$* measures the import tariff shock to industry pairs with similar inputs, and *$Tairff\text{-}OS_{ijt}$* is the import tariff shock to industry pairs with similar buyers. *$Uncertainty\text{-}IS_{ijt}$* and *$Uncertainty\text{-}IS_{ijt}$* are analogously defined using trade policy uncertainty shock instead of import tariff shock. See detailed definition in section 3.2. We control for the acquirer-year, target-year, and industry-pair fixed effects (*ij,it, jt*). Robust standard errors clustered at industry-pair level. * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table 3. Robustness

	$Dummy_{ijt}$				*$LogN_{ijt}$*			
	(1)Flexible	(2)ss<1%	(3) sector pairwise	(4) cossim	(5)Flexible	(6)ss<1%	(7) sector pairwise	(8) cossim
$Tairff\text{-}IS_{ijt}$		0.0654**	0.0680**			0.0525*	0.0568**	
		(0.0283)	(0.0295)			(0.0269)	(0.0268)	
$Tairff\text{-}CIS_{ijt}$				0.0116***				0.0094**
				(0.0040)				(0.0038)
$1999{*}IS\_T01_{ijt}$	-0.0031				-0.0000			
	(0.0111)				(0.0103)			
$2000{*}IS\_T01_{ijt}$	0.0291				0.0255			
	(0.0293)				(0.0258)			
$2001{*}IS\_T01_{ijt}$	-0.0018				0.0019			
	(0.0113)				(0.0127)			
$2002{*}IS\_T01_{ijt}$	0.0540				0.0266			
	(0.0377)				(0.0379)			
$2003{*}IS\_T01_{ijt}$	0.1099**				0.0809*			
	(0.0509)				(0.0486)			
$2004{*}IS\_T01_{ijt}$	0.1491***				0.1183**			
	(0.0488)				(0.0477)			
$2005{*}IS\_T01_{ijt}$	0.1361***				0.1378***			
	(0.0483)				(0.0508)			
$2006{*}IS\_T01_{ijt}$	0.1309***				0.1025**			
	(0.0462)				(0.0450)			
$2007{*}IS\_T01_{ijt}$	0.1894***				0.1985***			
	(0.0537)				(0.0559)			
Controls	*$Tairff\text{-}OS_{ijt}$, $Uncertainty\text{-}IS_{ijt}$, $Uncertainty\text{-}OS_{ijt}$*							
Fixed Effects	*ij, it, jt*							
N	139,210	125,040	134,890	139,210	139,210	125,040	134,890	139,210

Note: Column (1) runs the flexible estimation to check the parallel pre-trends, with specification in section 3.2.2. Columns (2) keeps industry pairs with supply share less than 1% to tease out vertical integrations more conservatively. Columns (3) uses a coarser classification of industry to define diversifying deals. Column (4) uses cosine similarity to define all similarity measures to check the robustness. Columns (5)-(8) are corresponding tests using as *$LogN_{ijt}$* dependent variable. All regressions include *$Tairff\text{-}OS_{ijt}$, $Uncertainty\text{-}IS_{ijt}$, $Uncertainty\text{-}OS_{ijt}$* as controls and account for the acquirer-year, target-year, and industry-pair fixed effects. Robust standard errors clustered at industry-pair level. * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table 4. Mechanism

	$Dummy_{ijt}$			$LogN_{ijt}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Tairff-IS$_{ijt}$	-0.0284	0.1093***	0.1151***	-0.0406	0.0893**	0.0962***
	(0.0354)	(0.0396)	(0.0369)	(0.0381)	(0.0360)	(0.0335)
shDf-Tairff-IS$_{ijt}$	0.1996***			0.1916***		
	(0.0501)			(0.0527)		
shRD-Tairff-IS$_{ijt}$		0.1794*			0.2028**	
		(0.0985)			(0.0992)	
shPT-Tairff-IS$_{ijt}$			0.1210***			0.1314***
			(0.0361)			(0.0373)
Controls	*Tairff-OS*$_{ijt}$, *Uncertainty-IS*$_{ijt}$, *Uncertainty-OS*$_{ijt}$					
Fixed Effects	*ij,it,jt*					
N	139,210	139,210	139,210	139,210	139,210	139,210

Note: *shDf-Tairff-IS*$_{ijt}$ measures the intensity of the tariff shock on differentiated common inputs. *Elas-Tairff-IS*$_{ijt}$ measures the intensity of the tariff shock on common inputs with higher elasticity of substitution. *shRD-Tairff-IS*$_{ijt}$ measures the intensity of the tariff shock on common inputs that are more R&D-intensive. *shPT-Tairff-IS*$_{ijt}$ measures the intensity of the tariff shock on common inputs that are more patent-intensive. See more details in section 3.3. Robust standard errors clustered at industry-pair level. * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Appendix.

Table A1. Summary statistics of main variables

	Mean	Std. Dev.	min	max	N
$dummy_{ijt}$	.007	.084	0	1	139210
$logN_{ijt}$	.007	.089	0	3.093	139210
IS_{ijt}	.017	.021	0	.494	139210
OS_{ijt}	.02	.039	0	.576	139210
$Tariff\text{-}IS_{ijt}$	.024	.042	0	.826	139210
$Tariff\text{-}OS_{ijt}$	.014	.039	0	.957	139210

Table A2. Correlation of main variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1) $dummy_{ijt}$	1.000					
(2) $logN_{ijt}$	0.959	1.000				
(3) IS_{ijt}	0.029	0.029	1.000			
(4) OS_{ijt}	0.021	0.020	0.143	1.000		
(5) $Tariff\text{-}IS_{ijt}$	0.055	0.054	0.448	0.071	1.000	
(6) $Tariff\text{-}OS_{ijt}$	0.034	0.034	0.255	0.199	0.258	1.000

Table A3. Tariff and Change in Input Similarity

Dep: $dIS0702_{ij}$	(1)	(2)	(3)	(4)
IS_T01_{ij}	*0.0733****	*0.0800****	*0.0787****	*0.0820****
	(0.0091)	*(0.0084)*	*(0.0224)*	*(0.0223)*
IS_col2_{ij}			*-0.0006*	*-0.0002*
			(0.0025)	*(0.0025)*
Fixed Effects	*No*	*i,j*	*No*	*i,j*
N	6006	6006	6006	6006

Note: The dependent variable $dIS0702_{ij}=IS07_{ij}-IS_{ij}$. with IS_{ij}, and $IS07_{ij}$ denoting the input similarity based on 2002 and 2007 IO table, respectively. IS_T01_{ij} measures the intensity of tariff reduction on common inputs of industry *i* and j as in the flexible estimation, and IS_col2_{ij} is defined analogously using the trade policy uncertainty measured by column 2 tariffs. Columns (1) shows that industry-pairs with common inputs that experienced larger tariff reductions (IS_T01_{ij}) tend to have a higher $dIS0702_{ij}$ and therefore a higher input similarity in 2007 ($IS07_{ij}$). The result is robust when we include the industry fixed effects in column (2), and when we further control for IS_col2_{ij} in column (3) and (4). * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table A4. Correlation of Tariff Shock with Input Specifity

Variables	(1) $lnT01_i$
(1) $lnT01_i$	1.000
(2) $shDf_i$	-0.068
(3) $shRD_i$	0.096
(4) $shPT_i$	0.298

Table A5. Regression of Tariff Shock on Input Specifity

	$lnT01_i$		
	(1)	(2)	(3)
$shDf_i$	-0.3448		
	(1.0352)		
$shRD_i$		0.4238	
		(0.3189)	
$shPT_i$			1.1728***
			(0.3429)
constant	3.5238***	3.0521***	2.9586***
	(1.0122)	(0.1515)	(0.1377)
N	79	80	80

Note: The variables are defined at io industry level. The variation in the number of observations is due to unmatched industries with tariff shocks but not corresponding input specificity measures. Robust standard errors clustered at io industry level. * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.