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Product-Market Competition and Resource Redeployment in Multi-Business Firms

Raffaele Morandi Stagni
ORCID: 0000-0003-4835-4564
Calle Madrid 126 - 6.0.37
Department of Business Administration
Universidad Carlos III de Madrid
28903 Getafe (Madrid) Spain
raffaele.morandi@uc3m.es

Juan Santaló
ORCID: 0000-0002-0339-3343
Calle Alvarez de Baena 4
Strategy Department
IE Business School/ IE University
28006 Madrid, Spain
juan.santalo@ie.edu

Marco Giarratana
ORCID: 0000-0002-0015-6529
Calle Alvarez de Baena 4
Strategy Department
IE Business School/ IE University
28006 Madrid, Spain
marco.giarratana@ie.edu

Corresponding author: Raffaele Morandi Stagni

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RESEARCH SUMMARY: This article investigates how diversified firms reallocate internal non-scale free resources when one of their product business units (BUs) experiences increased exposure to international competition driven by a sharp decrease in trade tariffs. On average, firms tend to fight, by reallocating resources toward the BU affected by the trade shock and away from other BUs within the same firm. Two variables moderate this first-order effect with opposite signs. The level of sunk costs of the assets allocated to the BU affected by the shock is a positive moderator of resource reallocation to it. The presence of technological synergies between the BU affected and the rest of BUs instead moderates the relationship negatively. This negative moderation seems to only take place when competition *increases* the value of technology as a competitive resource.

MANAGERIAL SUMMARY: An important question in the strategic decision-making process of diversified firms is how to react to competitive threats that affect one business unit but not the others. Should managers allocate more resources to the affected business or should they instead reduce their commitment and use the same resources in the remaining operating sectors? In this article we examine firms' reallocation decisions following increases in foreign competition due to import tariff cuts. Our results show that firms tend to allocate more resources to the business affected by the tariff cut and less to the businesses unaffected. Furthermore, we find evidence that this behavior is positively associated with performance.

INTRODUCTION

Unlike specialized firms, diversifiers can create value by redeploying scarce resources across the business units (BUs) they use to compete in different product markets (Helfat and Eisenhardt, 2004). Levinthal and Wu (2010) label resources "non-scale free" if they cannot be shared simultaneously by two distinct BUs but can be reallocated across BUs in different time periods by corporate headquarters. The redeployment process for such non-scale free resources generates intertemporal economies of scope, as long as diversified firms react promptly and efficiently to altered market conditions.

Prior literature illustrates the effects of negative demand-side shocks, for which both theory and evidence indicate that the optimal response is a reallocation of resources away from the sector suffering the decline in demand (Levinthal and Wu, 2010; Lieberman, Lee, and Folta, 2017; Wu, 2013). For example, Lieberman et al. (2017) leverage a theoretical model and descriptive statistics from the telecommunications industry to show that related diversifiers are more likely to speed up their exit from businesses that fail to meet demand expectations, through redeployment. Wu (2013) reports, using hazard and logistic regressions, that firms in cardiovascular medical device segments exhibit diversification patterns in which they abandon (enter) submarkets with declining (growing) demand.

In their work, Levinthal and Wu (2010, p. 784) also point out that opportunity costs in resource allocation depend not only on demand conditions, but also on "competitive conditions in alternative product markets". This in turn raises the question: are firms' reactions to competitive threats the same as in the case of declining demand? At first sight, the answer should be affirmative, because both shocks decrease firms' expected future profits. However, in the case of competitive shocks compelling arguments exist for increasing investments in the sectors affected. In this article, we consider the effect of increased competition that influences one product market of a diversified firm on how it subsequently reallocates its resources. As in the demand case, a firm could fight or flee; if it decides to confront the competitive threat, a BU could seek to discourage potential entrants by indicating its willingness to engage, for example, in a price war (Lieberman and Montgomery, 1988), or it might invest in differentiation efforts to insulate its profit margins from competition (Fernández-Kranz and Santaló, 2010; Flammer, 2015).

To investigate these potential outcomes, we exploit exogenous changes in product market competition as a main source of industry variation and study how diversifiers might improve (or not) their overall performance by redeploying non-scale free resources toward BUs that face increasing competitive pressure. Our empirical setting features a sharp decrease in import tariff rates for a particular sector; prior literature has reported that tariff changes impose considerable impacts on firms' markets and strategies (Flammer, 2015; Frésard, 2010; Frésard and Valta, 2015). In this context, we examine the reallocation of financial (cash) resources, for two reasons. First, financial resources are non-scale free, in that their use in one BU prevents their deployment in another. Second, cash transfers are visible strategic actions that potential rivals can use as credible signals that the firm is allocating any type of non-scale free resource toward a particular BU.[1] As Kim and Bettis (2014, p. 2056) note, "cash is a highly flexible form of credible threat to deter competitors," and cash transfers can enhance a BU's ability to compete, such that they function as effective entry deterrence devices.

We find that after an increase in international competition due to tariff shocks, a firm redeploys financial resources toward the affected BU and away from its other BUs. This strategy is associated with value creation. Our data indicates that, on average, diversified firms increase their allocation of resources to a BU directly affected by a reduced trade tariff by 3.4 percent of their average segment assets. This increased resource allocation then translates into

[1] If the firm, or its corporate headquarters, allocates more skilled personnel to reinforce the affected BU or assigns it more marketing power in terms of resources and personnel, it implies more financial expenses for this affected BU, and we can track them using our subsequently detailed measure of financial resource allocation.

a 1.6 percent gain in the market-to-book value and a 5.9 percent gain in the market-to-sales value, at the corporate level. The findings thus suggest that diversified companies respond to competitive shocks by fighting, which ultimately leads to better corporate performance (e.g. Deb, David, and O'Brien, 2017; Derfus *et al.*, 2008).

We explore two idiosyncratic characteristics of the firm and its BUs that may influence this first-order effect. First, we test how the amount of sunk assets invested in a BU influences the strength and direction of a firm's competitive response. Second, we analyze potential substitution effects between synergies and redeployment. According to Sakhartov and Folta (2014, p. 1788), "the interdependence between synergy and redeployment is not expected to be positive because, … if [a firm] redeploys resources to one business, the value derived from synergy is reduced." We empirically confirm that these two factors exert opposite effects. That is, the extent of sunk assets invested in the affected BU is a positive moderator of reallocation, whereas the presence of technological synergies acts as a negative moderator, but only when competition increases the value of technology as competitive resource.

With these analyses, our study explicates resource redeployments by diversified firms under changed competitive conditions. Among the factors theorized by Levinthal and Wu (2010) in the case of resource redeployment, we shift research attention away from the exogenous variation induced by demand dynamics (Lieberman *et al.*, 2017; Wu, 2013) and toward that ignited by competitive threats. In contrast with classical flight outcomes predicted by demand-based research, we find instead that diversifiers step up their investments in affected BUs, rather than reallocating their resources toward other BUs. We also replicate this scenario with an experiment administered to MBA students and we find the same result.

Granted, our theoretical explanation proposes relaxing the conventional assertion that external market conditions set the rates of return on resources employed by a focal BU, such that a negative (positive) shock always would be followed by divestiture (investment) (Helfat and Eisenhardt, 2004; Levinthal and Wu, 2010). With our complementary view, we propose that firms also might endogenously increase their marginal returns, through cash reallocation actions. In this respect, negative demand shocks may imply lower marginal resource returns (Helfat and Eisenhardt 2004; Wu, 2013), but increasing competitive pressures could augment the returns, especially in environments with a constant overall demand, and stiff competition on market shares (Fosfuri and Giarratana, 2009). Finally, our proposed moderators are not novel per se (Lieberman *et al.*, 2017; Sakhartov and Folta, 2014), yet we consider them from a competitive dynamics perspective for the first time. In so doing, we provide initial empirical evidence of a substitution effect between technological synergies and non-scale free resource redeployment (Lieberman *et al.*, 2017; Sakhartov and Folta, 2014).

THEORY

Review

Resource redeployment is fundamental to diversified firms' value creation and destruction processes. These firms persist and thrive only if they are more efficient than external markets in reallocating their resources among businesses (Folta, Helfat, and Karim, 2017). An alternative view suggests diversified firms are manifestations of managerial opportunism, which survive only in environments with weak competition (Giroud and Mueller, 2011).

From a bird's-eye view, the strategic option to withdraw resources from one BU and allocate them to another represents a different value-creating mechanism, separate from the mainstream conceptualizations of resource synergy (Rumelt, 1982; Silverman, 1999; Teece, 1982). Synergies stem from contemporaneously shared resources with unlimited capacity, but resource reallocation is possible only if assets have some opportunity cost (i.e., non-scale free resources; Levinthal and Wu, 2010).

Previous literature mainly has sought to understand how diversifiers use resource redeployment in response to adverse demand conditions (Anand and Singh, 1997; Levinthal and Wu, 2010; Lieberman *et al.*, 2017), such as when Wu (2013) demonstrates that in mature markets, in which growth in a firm's capabilities exceeds growth in demand, profit maximization might require sacrificing the performance of part of the organization. If diversifying firms transfer non-scale free resources from existing BUs to one operating in a new product market, the performance of those existing BUs could be negatively affected, even if the firm's overall profitability increases. Lieberman *et al.* (2017) predict that the value of related diversification might stem from the firm's ability to exit more quickly (because of higher asset redeployability) from businesses that fail to meet demand expectations. These studies thus establish that the optimal response of firms operating in environments that experience declining demand is to divert resources away from the affected product market. These studies also assume that corporate headquarters are profit maximizers.

Yet Levinthal and Wu (2010) further theorize that, beyond demand conditions, a vast array of factors can affect the opportunity costs associated with reallocating resources—including the level of competitive intensity in the market. We address this point by investigating the effect of significant increases in competition that affect one of the BUs of a diversified firm on the resource reallocation that follows. As an illustration, consider the case of MagneTek. In 1995, it experienced a significant increase in competition in its "Lighting Products" market (standard industrial classification [SIC] code 3612), which accounted for 42 percent of its sales in 1994. This increase in competition resulted from a 51 percent reduction of the import tariff rate applied to products by foreign competitors, as described in MagneTek's 1996 10-K report: "During fiscal 1996, the Company experienced lower demand and a significant deterioration in operating results in [light product business], due largely to a substantial reduction in utility related incentive programs and increased competition.… The Company conducted a review and analysis of actions … to reflect costs associated with repositioning operations" (see https://www.sec.gov). These "repositioning operations" involved a redistribution of resources, but toward which BU? At least for MagneTek, the resources went to the lighting products BU, which helped finance a consolidation of operations, as well as new practices aimed at responding better to customers' needs, providing better quality, and lowering defect rates (e.g., Demand Flow Technology, Six Sigma).

Hypotheses

As the Magnetek example illustrates, unlike environmental changes that lower demand, competitive shocks might increase or decrease the marginal value of resources applied to a particular sector (Aghion *et al.*, 2005; Raith, 2003), so they might induce reallocations toward or away from an affected BU. A reallocation of resources away from a troubled BU reflects the canonical redeployment logic in the presence of detrimental demand conditions, corresponding to a flight option (Levinthal and Wu, 2010; Lieberman *et al.*, 2017; Wu, 2013). However, corporate headquarters also might opt to increase resource allocations toward the affected BU. This fight option channels more resources to the BU, to preserve and increase its future profitability by enabling this BU to pursue preemptive actions that increase entry barriers to the sector or warn potential entrants of its willingness to engage in aggressive behavior (e.g., price war; Lieberman and Montgomery, 1988)[2].

Kim and Bettis (2014) argue that cash is a strategic asset that can deter threats from both current and potential rivals. Cash holdings both increase the uncertainty of success and lower expected returns for a new entrant. For example, a financially constrained entrant facing a cash-rich incumbent may be deterred by the threat of predatory pricing strategies (Benoit, 1984). With the assumption that cash allocations across BUs are visible to external actors, we designate cash transfers as credible signals to the external environment. With these increased resources, for example, the BU might pursue process innovations to reduce costs (Scherer and Ross, 1990)

[2] Our interviews, available on request, with executives at two large Italian manufacturing firms suggest that this behavior is perceived as a sort of baseline response. The CEO of one of the companies affirmed that "generally speaking if we are in a product-market is because we want to remain in it. I cannot think of a scenario where we would react to a competitive challenge by backing off".

or achieve product differentiation by investing in more insulating mechanisms within its market niche (Aghion *et al.*, 2005; Fernández-Kranz and Santaló, 2010; Flammer, 2015). It is worth noting that we focus on cash transfer because it is a highly visible part of a firm redeployment actions. Often however, cash is a proxy of internal transfer of other key resources, whose cost is now imputed to the receiving BU. Among the firms that we interviewed for example, top managers and sales representatives could be redeployed to respond to competitive threats, with the consequence that the cost of their salaries will be imputed to the receiving BUs.

In theory, given an increase in entry threat, both the "fight" and "flight" alternatives are consistent with value creation. The canonical Industrial Organization literature (Fudenberg and Tirole, 1984) postulates that incumbents can strategically vary their investment policies on a continuum between an aggressive or an accommodating attitude towards potential competitor's entry. Firms will over invest or under invest depending on a) whether investment makes the incumbents look tough or soft, and b) whether the competitive interactions that characterize the market are strategic complements or substitute[3]. Stepping up (down) investment to deter entry is more likely when it makes firms look tough (soft) and the competitors' actions are strategic substitutes (complements).

Which behavior is more probable in our case? Fresard and Valta (2016) and Fresard (2010) explicitly conclude that aggressive investments after a trade liberalization make companies appear tough, provided they are not financially constrained. Diversified firms tend to be less financially constrained, because imperfect correlations among the investment opportunities for their various BUs support cross-subsidization (Kuppuswamy and Villalonga, 2016). Furthermore, Kedia (2006) and Fosfuri and Giarratana (2009) show that competitors' actions tend to be strategic substitutes when competitive entry does not increase demand, but it

[3] Investment makes an incumbent look though if it decreases the expected future profits of an entrant. In the opposite case it makes it look soft. Firms actions are strategic complements if an increase in production by one firm increases the marginal revenues of the others. Vice versa, actions are strategic substitutes if an increase in one firm's output decreases the marginal revenues of the rest of competitors, thus decreasing their incentive to produce.

does increase the competition for market share. We safely assume that a tariff shock does not increase overall demand significantly[4]. Because investments make diversified firms appear tougher and their competitive actions are strategic substitutes, the marginal returns of investing valuable non-scale free resources should increase since they preempt entry (Fudenberg and Tirole, 1984), leading to aggressive resource redeployments toward BUs affected by a competitive threat. Therefore, we hypothesize:

H1: Diversified firms reallocate non-scale free resources to business units threatened by a competitive threat and away from other, unaffected business units.

Idiosyncratic organizational and environmental characteristics inevitably create conditions in which this first-order effect could be stronger or weaker. For example, the fight option requires credibility, because deterrence strategies are only effective in the presence of a credible and binding commitment. Thus, resource redeployments might depend on the extent to which the company already has sunk investments in the affected sector (Sutton, 1991). In the absence of sunk costs and when entry in a sector is less costly, an entrant may rationally forecast that the incumbent will accommodate its move by redeploying resources elsewhere. Deterrence is unlikely (Salop, 1979). In contrast, the presence of sunk costs, because they reduce the overall value generated by redeployment, function as an exit barrier. With their theoretical model and descriptive data, Lieberman *et al.* (2017) conclude that when sunk costs are low, new entrants require a comparatively lower expected return to enter a sector and a comparatively higher minimum return to remain.

Furthermore, high levels of sunk cost are normally linked to resources that are specialized to perform specific functions. In our interviews, executives pointed out that on the one hand, the presence of such resources motivates the competitive reaction (because of the fear of losing the investment), while on the other it enables it, by increasing the effectiveness of the

[4] As outlined in the methodology section, we empirically confirm this assumption with regressions that test the effect of tariff shocks on internal demand and by reviewing the performance and survival rates of incumbents after the tariff variation.

competitive response. We thus argue that if firms react to a competitive threat by increasing investments in BUs with already high levels of sunk costs, it likely appears more credible to competitors, as a signal of long-term commitment. The higher (lower) the level of sunk costs, the more (less) likely additional investments will be interpreted as serious threats (Fudenberg and Tirole, 1984). Sunk cost increases the marginal returns on resources, due to the higher credibility of a fight commitment issued in response to a new competitive threat. Thus, if potential new competitors correctly interpret the signal, the incumbent firm earns higher profits in the new competitive conditions. Therefore, we hypothesize:

> *H2: When there is a competitive threat, the level of sunk costs already invested in the sector of the threatened business unit positively affects the amount of non-scale free resources reallocated toward the threatened business unit.*

Intertemporal economies of scope generated by the redeployment of non-scale free resources (Helfat and Eisenhardt, 2004) and intratemporal economies of scope created by synergies of scale free resources also could induce "conflicting value-creating mechanisms" (Sakhartov and Folta, 2014: 1783). Sakhartov and Folta (2014) hypothesize that resource reallocation and synergy are, to a certain extent, substitute mechanisms. These authors explain that "synergy adds value when resources are contemporaneously shared across markets, resource withdrawal involved in redeployment compromises returns from synergy" (Sakhartov and Folta, 2014: 1793), because the redeployment of non-scale free resources constitutes an optimization process that implies a complete exit from a sector, to enter a new industry (Helfat and Eisenhardt, 2004). If diversified firms exit one sector by reallocating all their assets to a new industry, any benefit of sharing resources contemporaneously ceases. Moreover, withdrawing resources from one BU and reallocating them to another might jeopardize the firm's capability to renew or expand the value of its scale free assets. Henderson and Cockburn (1996) show that sustaining a wide array of R&D programs is essential for capturing internal knowledge spillovers that exert significant positive effects on overall technology production. The effect of R&D programs' scope also is stronger and more significant than that of their scale. Our own interviews are in line with this reasoning. As the CEO of an Italian business-to-business manufacturing firm pointed out, the critical issue for them is not to lose a key corporate account completely. Information is shared across BUs and, as long as they are still present in the account, they become aware of the client new product's initiatives and of the requirements of its procurement office. Under this logic, even if a BU has temporarily lost part of its sales in the account, it will still be able to identify new opportunities and to obtain insights that will help it to better tailor its future proposals. Cross-selling different product lines is thus a key advantage that ensures the continuous flow of valuable information and that, as a consequence, helps in directing the R&D effort of each division and in extracting the maximum value from it.

These arguments suggest that in the face of a competitive threat, reallocating resources from the R&D program of some BUs to that of a BU affected by competition might destroy value, even if the total scale of the R&D effort remains the same. That is, in the presence of synergies across BUs, we predict that the redeployment of resources is more costly, because its function as an entry deterrence signal is partially compromised by the reduced synergy advantages.

In addition, when its scale free resources are shared, a firm that takes the fight option can devote more non-scale free resources to renewing and improving the shared scale free resource (e.g., technology, brand image), which usually is centralized. It thus has less need to move its resources toward the affected BU. This argument echoes Shaver's (2006) finding that synergies propagate spillovers across BUs. If a scale free resource exhibits greater marginal value, due to more competition in the sector in which it is applied, marginal returns increase for the firm overall. If some redeployment is absorbed by centralized, scale free resources, fewer resources are channeled toward the affected BU. In summary, the relative gains of redeploying resources toward an affected BU are lower when synergies exist that increase returns to a centralized resource allocation. Thus, it should channel fewer resources toward a BU that exhibits more synergies with other BUs in the firm.

A clear example is IBM in the 1990s. In 1999, IBM maintained six segments: Computer Storage Devices (SIC 3572), Electronic Computers (SIC 3571), Computer-Related Services (SIC 7379), Computer Integrated Systems Design (SIC 7373), Prepackaged Software (SIC 7372), and Business and Credit Institutions (SIC 6159). Its explicit strategy was to integrate solutions for companies (Gerstner, 2002). This one-stop shop approach implies that IBM could respond to competitive threats from low-cost competitors in one BU by improving its service and brands, centralized and applied across sectors. For example, IBM transferring top management personnel to improve its Computer Services, should also enhance the IBM business of selling computers. Assuming IBM chooses the fight option, the amount of resources it would need to transfer to a BU in danger, such as Electronic Computers, would be lower if its BUs were related. The entry deterrence implications of allocating more resources to the threatened BU similarly could be achieved by increasing investments in the overarching IBM brand and service levels. We thus hypothesize:

H3: When there is a competitive threat, synergies between a threatened business unit and the rest of the business units of the firm negatively affect the amount of non-scale free resources reallocated to the threatened business unit.

DATA & METHODOLOGY

Data sources

We use import tariff data compiled by Feenstra (1996), Feenstra, Romalis, and Schott (2002), and Schott (2010) to capture variations in the intensity of foreign competition faced by U.S.

firms. Each product category imported to the United States is identified through a ten-digit harmonized system (HS) code defined by the World Custom Organization. Feenstra (1996) and Schott (2010) map HS product data into aggregated, four-digit SIC codes. We use these four-digit SIC codes (or SIC4) to define industries. The resulting data are available for 1974–2005 for manufacturing SICs (2000–3999), so our analysis is restricted to manufacturing BUs. Of the 507 industries in the original database, 482 feature diversified firms that also are included in the COMPUSTAT Segment database.

For each industry-year, we calculate the *ad valorem* tariff rate as a ratio between the duties collected by U.S. Customs and the free-on-board value of imports. Tariff rates tend to fluctuate from year to year, but the average tariff change is typically small and economically insignificant (Flammer, 2015). To distinguish minor tariff fluctuations from important tariff reductions, we compare the tariff change for a given industry-year with the average tariff change for the same industry calculated over the whole sample period. Similar to Frésard (2010), Frésard and Valta (2016), and Flammer (2015), we define a negative tariff change as a tariff cut only if it exceeds three times the average tariff variation for its industry. We also ignore tariff variations between 1988 and 1989, because of a change in the import coding procedure. To ensure that we do not simply observe transitory tariff fluctuations, each tariff cut cannot be preceded or followed by equivalently large tariff increases. Finally, to ensure that the identified events have economic significance, we require the tariff rate in the year before the tariff cut to be at least 1 percent.

We focus on events starting from 1977, in line with the 1976 start date of the COMPUSTAT Segment database; we require at least one year of data prior to any tariff cut. After filtering data according to these criteria, we retain 214 tariff cut events, the first in 1977 and the last in 2005. These events pertain to 170 unique industries. As Figure 1 shows, the events span the entire duration of the sample period, which helps ensure that our results are not driven by time-specific confounding factors, such as economic cycles. Figure 1 also reveals two large waves of trade liberalization: the first between 1980 and 1982, which is the direct result of the ratification of the General Agreement on Tariffs and Trade Tokyo round and the implementation of the U.S. Trade Agreement Act in 1979, and then a second wave in the early 1990s, produced by the ratification of the Free Trade Agreement between the United States and Canada in 1989, followed by the ratification of the North American Free Trade Agreement among the United States, Canada, and Mexico in 1994. On average, tariff cuts represent a 41 percent reduction of the tariff rate, compared with average tariff rates of 6.7 percent in the year prior to the event and 4.2 percent in the year after the event.

*******************Please insert Figure 1 about here*********************

A simple analysis of single-segment firms confirms that tariff shocks increase the intensity of market share competition and do not increase overall demand. On average, single-segment firms operating in a treated SIC4 code report a decrease of 7.8 percent in their market-to-book value (from 2.19 to 2.02) between the three years after and the three years before the negative tariff variation. Moreover, three years after the trade shock, around 15 percent of these firms disappear from COMPUSTAT. In a confirmatory analysis (available on request), we also consider whether tariff reductions have positive effects on total industry sales in the affected product markets,[5] but we find no such impact of the trade shock.

We obtain firm- and BU-level financial and accounting data from Standard & Poor's COMPUSTAT database. Our measure of sunk costs matches Kim and Kung's (2017) method; the data for its calculation are available on Hyunseob Kim's website. To compute our measure of scale free resource relatedness, we use the National Bureau of Economic Research (NBER) patent database (Hall, Jaffe, and Trajtenberg, 2001) for 1976–2006. It contains detailed information about patents the U.S. Patent and Trademark Office (USPTO) grants to firms, the

[5] We estimate sector fixed-effect regressions with year controls to test the effect of tariff cuts on both internal demand and total demand for U.S. producers. We estimate the regressions with a 10-year span, 5 years before to 5 years after the tariff cut events. The sector's internal demand is the natural log of the value of shipments plus imports, minus exports. Its total demand is the natural log of the value of shipments plus exports. None of these results is significant.

patent class (type of technology that patents contain), and changes in patents' ownership over time.

Methodology

We exploit the 214 identified tariff cuts to estimate the effect of competition on resource allocations. We form two samples, each composed of BUs belonging to diversified firms affected by a tariff cut matched with control BUs belonging to diversified firms not affected by tariff cuts. The first sample, the *BUs Directly Affected Sample*, comprises BUs that operate in an industry undergoing tariff cuts. The second sample, the *BUs Indirectly Affected Sample,* consists of BUs of a diversified firm that is experiencing a tariff cut but that are not directly affected by it in their specific operating market. This two-sample design enables us to obtain additional evidence of resource redeployments, by observing both inflows and outflows of resources from the BUs, affected and not, that belong to the same focal firm hit by tariff cuts. For example, if our Hypothesis 1 is confirmed, as a consequence of tariff cuts we expect to observe and increase in resource allocation to the treated BUs of the *BUs Directly Affected Sample*, and a decrease in resource allocation to the treated BUs of the *BUs Indirectly Affected Sample*.

The treatment variable *Tariff Cut* is a dummy, equal to 1 if either the owning firm (*BUs Indirectly Affected Sample*) or directly the BU (*BUs Directly Affected Sample*) experiences a tariff cut, and 0 otherwise. A detailed description of our methodology for sample formation is available in the Appendix at the end of the paper.

Matching

In our empirical strategy we first alleviate endogeneity concerns with our use of exogenous changes in import tariffs. However, it could be the case that import tariffs are more likely to be reduced in some industries than in others. For instance, import tariffs might more likely decrease in industries whose firms consider them less critical for their portfolio. If diversified firms care less about some industries, they will exercise less lobbying pressure and therefore it may be more likely that tariffs are decreased in that type of industries. If diversified firms are less committed to these industries, then it would also be much more likely that resources are reallocated away from them. Alternatively, it could be the case that import tariffs decrease could happen more likely in non-competitive industries that policy makers think that could greatly benefit from foreign competition. If these noncompetitive industries are populated by diversified firms that really care about them (because they are very profitable or any other reason), then it may be the case that the likelihood of an import tariff decrease would be positively associated to within firm resource allocation towards these industries. This line of thought would suggest a spurious positive correlation between the likelihood of import tariffs decrease and within firm resource allocation towards the affected BUs. More in general, if the characteristics of the affected industries, or the characteristics of the BUs and the firms that populate these industries, are not a random representation of the entire US manufacturing population, then our results could be biased.

To alleviate these concerns, we follow Flammer (2015) and Fresard (2010) and we utilize a matching procedure to find a control sample. The purpose of the matching is to minimize the differences between treatment and control groups along those dimensions that we believe to be the most likely to affect resource allocation. The intuition is that BUs with similar characteristics, similar historical levels of resource allocation, and that belong to firms with similar strategies and resources, constitute good counterfactuals to estimate what would have happened to our treated groups absent the tariff cut.

In particular, in our matching we pair each treated BU in our two samples with a control observation belonging to the same year and similar in terms of a set of relevant industry, firm, and BU characteristics. Each control observation operates in an industry similar to that of the corresponding treated observation. Because our treatments are defined at the SIC4 level, we cannot match observations based on the narrowest definition of industry; instead, we require matched observations to operate in the same two-digit SIC industry and serve the same type of customers (business-to-business vs. business-to-consumer). We rely on information published by Sharpe (1982) and Lev *et al.* (2010) to partition SIC industries according to the primary type of customer they serve. This procedure addresses two potential concerns. That is, we need the treated and matched observations to operate in industries with similar logics and dynamics, but we also need a sufficiently large pool of potential matches so that we can select observations based on firm and BU characteristics. Requiring control BUs to operate in the same three-digit SIC sector (or SIC3) of the treated observations would likely limit our ability to fulfill the second requirement.

Next, from the pool of candidates, we pick the nearest neighbor, according to the following characteristics, calculated using COMPUSTAT data: BU resource allocation, BU size, firm size, firm cash, firm leverage, and firm number of segments. In particular, BU resource allocation is the value of resource allocations over segment assets; both BU size and firm size are calculated as log values of sales; firm cash equals the log of cash and short-term investments; firm leverage is the ratio of debt over total assets; and the number of segments is simply a count variable of the firm's segments. For the first five variables, we take averages over the three years before the treatment. The number of segments refers to the count in the year of the tariff shock. The nearest neighbor is selected using the Mahalanobis distance calculated on all six matching characteristics.[6] Similar to Flammer (2015), we require the treated and matched observations to have data available for at least the year before and year after the treatment to be included.

[6] To prevent the same control observations from being selected multiple times, we use a randomization procedure. For each treated observation, we calculate its three nearest neighbors using the "mahapick" command in Stata 12. If the closest match is selected multiple times for different treated observations, we randomize among them to choose which observation will be assigned its second closest match, according to the "mahaselectunique" command in Stata 12.

The matching variables all are likely to influence resource allocations to BUs. Matching observations on the pre-treatment value of the resource allocation reduces noise due to the correlation of the dependent variable with its own lagged values. Matching on the number of segments ensures that the firms have a similar number of BUs competing for resources. Firm size and BU size influence the firm's ability to change its level of investment in the BU. Finally, firm cash and firm leverage capture its ability to use internal liquidity or additional debt to increase resource allocations to a BU. The Online Appendix discusses analytically the pros and cons of our choices in terms of the identification strategy.

The application of these criteria produces a *BUs Directly Affected Sample* that contains 1,598 observations (799 treated and 799 control), as well as a *BUs Indirectly Affected Sample* with 2,494 observations (1,247 treated and 1,247 control).

Dependent Variable

Cash is a non-scale free resource that is both easily redeployable and subject to opportunity costs. We assume that cash redeployment across BUs is a visible strategic action that could lead to credible entry deterrence. All the firms in our sample are public firms subject to stringent reporting requirements, so cash movements across BUs are visible in their mandatory accounting reports.

To capture within-firm transfers of resources, we use the difference between cash invested and cash generated. We follow Billet and Mauer (2003) to calculate the dependent variable, resource allocation, which we define as the difference between a BU capital expenditure and its own after-tax cash flow (ATCF). For every given sample year, we calculate the resource allocation for a BU *i* of firm *j* in year *t* as:

$$Resource\ Allocation_{i,t} = CAPEX_{i,t} - ATCF_{i,t}, \tag{1}$$

where $CAPEX_{i,t}$ and $ATCF_{i,t}$ are BU *i*'s reported capital expenditure and BU *i*'s after-tax cash flow in year *t*, respectively. The $ATCF_{i,t}$ is calculated as:

$$ATCF_{i,t} = (EBIT_{i,t} - I_{i,t})(1 - T_{i,t}) + D_{i,t}, \tag{2}$$

where $EBIT_{i,t}$ is BU i's reported earnings before interest and taxes, $D_{i,t}$ is BU i's reported depreciation and amortization expense, and $I_{i,t}$ and $T_{i,t}$ are BU i's imputed interest expense and BU i's imputed tax rate, respectively.[7]

For our empirical analysis, we focus on the change in resource allocation between periods before and after the tariff cuts. For each treated and control observation, we compute the difference between the BU's average resource allocation after the treatment minus the average resource allocation before the treatment. We follow Flammer (2015) and use a window of three years to calculate the averages.[8] Finally, to reduce the outliers' influence, we deflate the difference by the total segment assets, calculated as the average in the three years before the treatment. Therefore, our final dependent variable is:

$$\Delta Resource\ Allocation_{i,t} = \left(\sum_{x=t+1}^{t+3} \frac{R.Allocation_{i,x}}{3} - \sum_{x=t-1}^{t-3} \frac{R.Allocation_{i,x}}{3}\right) / \sum_{x=t-1}^{t-3} \frac{BUassets_{i,x}}{3}. \tag{3}$$

Using resource expenditures (CAPEX) as a proxy of resource allocation is straightforward, but subtracting resource generation (ATCF) from this value might create concerns, because ATCF partially depends on market conditions, not just managerial actions. Nevertheless, including the ATCF component is necessary to capture resource reallocation in our context for two reasons. First, including the ATCF allows us to capture a series of investments, other than in physical assets that would otherwise go undetected. For example, under U.S. Generally Accepted Accounting Principles (GAAP), most investments in

[7] The imputed interest expense $I_{i,t}$ is the product of BU i's reported sales and the median ratio of interest expenses to sales, calculated for all firms operating in business unit i's industry. The imputed tax rate $T_{i,t}$ is the median ratio of income taxes due to pre-tax income calculated for all firms operating in BU i's industry. We define business unit i's industry as the narrowest SIC grouping that returns at least five focused firms (Billett and Mauer, 2003).

[8] Taking the average of the dependent variable in the pre- and post-treatment periods, instead of using actual data points, is the solution that Bertrand, Duflo, and Mullainathan (2004) recommend to reduce the probability of false positives when dealing with a dependent variable with serially correlated outcomes.

advertising and R&D must be expensed in income statements and enter into calculations of ATCF. Second, corporate resources in diversified firms depend on the amount of cash flow generated by the units. To this regard an increase in spending in one BU can have consequences or not for the rest of the organization depending on the amount of resources it generates. For example, the increase in spending could be entirely self-financed (without the need for reallocation) if it happens in a period in which the ATCF is also growing. On the other hand, keeping the rate of investment in a BU at the same level despite the fact that the BU is suddenly generating fewer resources goes to the detriment of the rest of the organization. The corporate headquarter will in fact be left with fewer resources to allocate to the rest of its units. This latter action also sends a powerful signal to competitors as it manifests the willingness of the corporate headquarter to subsidize the BU's competitive standing even through a period of turmoil.

Independent Variables

In addition to the tariff cut dummy, we include sunk cost and technological relatedness as independent variables and moderators of the effect of tariff cuts. To estimate sunk costs at the BU level, we use an asset redeployability measure developed by Kim and Kung (2017).[9] The measure estimates the extent to which assets currently invested in one sector are specific to that sector or alternatively could be redeployed to other sectors. To calculate it, the authors use the 1997 Bureau of Economic Analysis (BEA) capital flow table, which breaks down expenditures on new equipment, software, and structures by 180 assets for 123 industries. To obtain a redeployability score at the industry level, Kim and Kung (2017) first calculate a redeployability measure for each asset class in the BEA table as the sum of the weights (market

[9] This measure can be downloaded from the website http://blogs.cornell.edu/hyunseobkim/asset-redeployability/. It is available for 1985–2015 for several manufacturing SIC4 industries. To avoid observation losses, if the proxy is not available for a specific SIC4, we filled in the missing value by computing a weighted average of the measure at the SIC3 level. Our sample starts in 1977, and we find low year-to-year variance in this measure, so we also fill the values of the missing years with the first estimate available. When we eliminate observations with missing values and their corresponding matched observations, the results remain very similar to those obtained after the substitution.

capitalization of firms in the industry) of industries that use the asset. Resource redeployability at the industry level is then computed by weighing the redeployability score of each asset class by the industry expenditure in the asset category. The measure further takes into account the extent to which firms' output in a given industry co-moves. High within-industry correlation in outputs arguably should reduce asset redeployability during industry downturns (Shleifer and Vishny, 1992). To calculate our proxy, we multiply the logarithm of the assets reported by the BU in the year of the shock by Kim and Kung's (2017) redeployability proxy. We then reverse-code the measure to obtain an estimate of sunk cost.

For the degree of technological relatedness between the affected BU *i* and the rest of the firm's BUs, we use the total amount of cross-citations between patents granted to companies operating in sector *i* and patents granted to companies active in the rest of the focal firm's operating product markets. Cross-citation measures have been used frequently to capture the extent of interorganizational knowledge flows (Mowery, Oxley, and Silverman, 1996; Schildt, Keil, and Maula, 2012). We follow a similar logic to capture the potential for intra-organizational knowledge sharing among a firm's BUs. We consider cross-citations between a sector pair as a proxy for the extent to which the two sectors share a similar technological base. More similar technological bases in the sectors in which two different BUs operate implies the firm is more likely to benefit by having its BUs share their knowledge. In turn, the firm likely conducts R&D relevant for the BUs at the corporate level (Hill, Hitt, and Hoskisson, 1992).

As a first step in the calculation, we attribute, to every patent in the NBER database, a SIC4 code, using the operating sector of the patent owner, as reported in COMPUSTAT.[10] Next, we compute a three-year rolling sum of the total amount of cross-citation between each industry pair. When more patents assigned to companies operating in two different SIC4 codes cite each other, the two industries likely are more technologically related. Formally,

[10] If a patent has multiple owners, we divide its weight among the operating sectors of the owners equally. If a patent belongs to a diversified firm, we divide its weight proportionally among the operating sectors of the firm by segment sales.

$$CrossCit_{A,B,t} = \sum_{t-3}^{t-1} C_{A\to B} + C_{B\to A}, \tag{4}$$

where $CrossCit_{A,B,t}$ is the total amount of cross-citation between a Sector A–Sector B pair, calculated in year t. $C_{A\to B}$ is the total number of times patents granted in a given year to companies operating in Sector A cite patents granted to companies operating in Sector B, and $C_{B\to A}$ is vice versa. Having estimated the level of the relatedness of each SIC4 pair, we calculate the level of relatedness of BU i as a weighted average by segment sales of the cross-citation between operating sector i and the other operating sectors of the firm. We take the natural logarithm of the resulting measure to reduce the influence of outliers. Therefore:

$$Technological\ Relatedness_{i,t} = \ln \sum_{\substack{Y=1 \\ Y\neq i}}^{N} CrossCit_{i,Y,t} * \frac{s_{Y,t}}{\sum_{\substack{X=1 \\ X\neq i}}^{N} s_{X,t}}, \tag{5}$$

where $Technological\ Relatedness_{i,t}$ is an estimate of BU i's technological relatedness in year t, N are the sectors in which the diversified firm to which BU i belongs operates, and $s_{Y,t}$ ($s_{X,t}$) indicates the sales of operating segment Y (X) in year t. This measure thus captures the extent to which BU i shares a common technological base with the rest of the firm's BUs. We compute it using total cross-citations between patents granted by the USPTO in the three years before the shock.

Control Variables

Five control variables coincide with our matching variables: firm size, firm cash, firm number of segments, firm leverage, and BU size. Furthermore, we include controls for changes in demand and changes in market uncertainty between the periods before and after the tariff cut. The demand change control variable reflects the percentage difference in the total size of the market. Market size is defined as the total sales of the firms operating in a given SIC4. Our control for changes in market uncertainty is the change in the standard deviation of the monthly returns of value-weighted portfolios of single-segment firms, built on the basis of their SIC4. All the data necessary for this proxy come from CRSP. Changes in demand and uncertainty affect the expected return and risk of investing in a market; therefore, they should be primary determinants of changes in investment policy. We control for whether the BU is operating in the primary sector of the firm, because these BUs might be subject to different resource allocation policies than other units. We control for whether the firm benefits from the presence of credit rating as an additional proxy for its ability to access external financial markets, which may enable it to avoid reallocation. The dummy variable rating takes a value of 1 if the firm has a Standard & Poor Domestic Long-Term Credit Rating available in the year of the shock, and 0 otherwise. We also control for analysts' coverage and whether the firm discloses its advertising and R&D expenses. In particular, we determine the total number of analysts in the year of the tariff cut that issue predictions about the firm's earnings (Shi, Connelly, and Hoskisson, 2017) for the period between t + 1 and t + 3. With two dummy variables, disclose advertising and disclose R&D, we capture whether the firm reports these expenses separately, in the year of the tariff cut. With the inclusion of analysts' coverage and the two dummies, we control for potential heterogeneity in the observability of firms' strategic actions. Finally, we include a set of controls for sector-level characteristics that might influence reallocation: market size, market profitability, market concentration (Herfindal index), percentage of diversified firms vs. single-segment competitors, and percentage of diversified firms operating in the sector for which it is the primary SIC. All these controls are calculated as averages across the three years preceding the shock.

*******************Please insert Table 1 about here*********************

Table 1 reports the descriptive statistics of the matching and control variables for both samples and for each group of treated and control BUs. In the two samples, treated and control observations are almost identical in their means and distributions. Similarity along these dimensions ensures that the control BUs provide a good counterfactual for what would have happened to our dependent variable in the absence of an import tariff cut. Figure 2 depicts the trends in average resource allocations in the years between t – 3 and t + 3 (where t is the year of the tariff cut) for both samples and the treatment and control groups. As these data show, the treatment and control groups exhibit similar trends across both samples in the years t – 3 to t – 1, further confirming the validity of our matching procedure. The sudden variation in both samples between t – 1 and t + 1 offers evidence that the economic impact of the tariff cut is concentrated in the years immediately before and after the treatment.

*****************Please insert Table 2, Figures 2.a & 2.b about here*****************

Table 2 contains the pairwise correlations between the variables of interest for both the *BUs Directly Affected Sample* and the *BUs Indirectly Affected Sample*. The highest correlations are between variables that grow together with the size of the organization (e.g., firm cash and firm sales, with a correlation coefficient of .87). These variables only appear together in the analyses as controls. The maximum variance inflation factor across regressions is 7.2.

General Estimation Model

To measure the effect of a tariff cut on the resource allocation received by a firm's BUs, we estimate the following regression on the *BUs Directly Affected Sample* and the *BUs Indirectly Affected Sample*:

$$\Delta Resource\ Allocation_{i,t} = \alpha_t + \beta_1 \times Tariff\ Cut_{i,t} + \beta_2 \times Sunk\ Cost_{i,t} + \beta_3 \times Tariff\ Cut_{i,t} \times Sunk\ Cost_{i,t} + \beta_4 \times Technological\ Relatedness_{i,t} + \beta_5 \times Tariff\ Cut_{i,t} \times Technological\ Relatedness_{i,t} + \gamma' \mathrm{X}_{i,t} + \epsilon_{i,t}, \quad (6)$$

where α_t are year fixed effects; *Tariff Cut* is the treatment dummy variable, equal to 1 if the observation belongs to the treatment group and 0 if it belongs to the control group; *Sunk Cost* and *Technological Relatedness* are the two moderator variables; ϵ is the error term; and *X* is a vector of control variables that includes five of the six characteristics used for the matching (firm size, firm cash, firm number of segments, firm leverage, and BU size; we exclude BU's resource allocation because the dependent variable is the difference between the periods after and before the tariff cut), as well as the twelve controls outlined in the previous section.

Our two moderator variables, *Sunk Cost* and *Technological Relatedness*, are defined at the affected BU level, and thus their value is constant across all the BUs of the same firm. In line with our theory, the characteristics of the BU affected by a tariff cut influence the extent of resource redeployment, and consequently the impact on the rest of the BUs of the focal firm. We cannot perfectly replicate this procedure for control firms, because they do not own affected BUs. Thus, *Sunk Cost* and *Technological Relatedness* of control firms correspond to the value of the BU that is the most similar to the one directly affected by the tariff cut in the matched treated firm. In practice, this entails that for control BUs in the *BUs Indirectly Affected Sample* we have to perform an additional step of matching to find the appropriate values. The Appendix at the end of the paper describes in detail our matching methodology for the formation of the two samples. The Online Appendix analytically examines the implication of the methodology on bias and measurement error in the estimation of the effect of moderators for the *BUs Indirectly Affected Sample*.

We cluster standard errors at the two-digit SIC level. The coefficients of interest are β_1, β_3, and β_5, and we expect each of them to take opposite signs in the two samples if an increase in competition triggers a reallocation of resources.

***********************Please insert Table 3 about here************************

RESULTS

Table 3 presents the results of the analyses of the *BUs Directly Affected Sample* and the *BUs Indirectly Affected Sample*. In all regressions, the dependent variable is the change in total resource allocation three years after compared with three years before the treatment, deflated by segment assets. All the reported models include control variables and year fixed-effects.[11] We cluster the standard errors at the two-digit SIC level.

We start by examining the main effect of competition on resource reallocation activity. According to Hypothesis 1, tariff cuts should cause a reallocation of resources from the BUs operating in stable market conditions to those affected by the shock. The results support this prediction; the coefficient of the tariff cut dummy at the BU level is positive in the analyses on the *BUs Directly Affected Sample*, while the coefficient of the tariff cut dummy at the firm level is negative in the analyses on the *BUs Indirectly Affected Sample*. For the *BUs Directly Affected Sample*, the coefficient lies between .034 ($p = .031$), in the model that only tests the main effect of the tariff cut, and .077 ($p = .020$), in the model that includes the relevant interactions. For the *BUs Indirectly Affected Sample*, the coefficient instead lies between -.017 ($p = .057$), in the model including only the tariff cut dummy, and -.055 ($p = .002$), in the model including the interactions. If we consider those models that include only the tariff cut dummy (Models 1 and 5), we find that on average, diversified firms increase their allocation of resources to BUs directly affected by a tariff cut by 3.4 percent of their average segment assets. They correspondingly decrease the allocation of their resources to other BUs by 1.7 percent of their average segment assets. The decrease in resource allocations to BUs unaffected by the tariff cut is less than the corresponding increase to BUs affected by it, consistent with the characteristics of our sample firms, which have on average 3.26 BUs. Thus, firms appear to spread the burden of financing the affected BU across multiple other units.

Hypothesis 2 predicts that greater sunk costs invested in the BU affected by the tariff cut also leads to more resources reallocated to it after the shock. Models 2 and 6 offer support for this hypothesis, in that the coefficient of the interaction between the *Tariff Cut* dummy and *Sunk Cost* is positive with the *BUs Directly Affected Sample* (coeff. = .086; $p = .039$) but

[11] Out of space considerations, we report only the coefficients of the variables of interest. The full tables containing the estimates of the coefficients for the control variables are available on request.

negative with the *BUs Indirectly Affected Sample* (coeff. = -.069; p = .002). Figure 3 plots the total effect of a tariff cut on resource reallocations at different sunk costs levels, using the coefficients from Models 2 and 6. It reveals that the total effect reverses when the affected BU has a sunk cost value below -.9, which corresponds to the 15th percentile in the sample of BUs.

The analysis of the effect of technological relatedness on reallocation partially support Hypothesis 3, such that the interaction between technological relatedness and the tariff cut is positive with the *BUs Indirectly Affected Sample*, as expected (Model 7, coeff. = .012; p = .022), but has a high standard error in the analysis with the *BUs Directly Affected Sample* in Model 3. As a possible explanation, we posit that technological relatedness might influence resource reallocation only if the tariff cuts do not jeopardize the value of technological synergies. In this case, the incentives for not engaging in reallocation, as we described in the theory section, remain in place. However, if the tariff cut decreases the value of technology, the BU must invest in other differentiation sources, and it needs a greater resource endowment. We test this explanation by separating out sectors in which tariff cuts increase the value of technology from those in which tariff cuts decrease its value.[12] Then we form one *BUs Directly Affected Sample* and one *BUs Indirectly Affected Sample* for each type of sector, using our previously described procedure. As we show in Table 4 and as expected, the negative moderation by technological relatedness arises only when tariff cuts increase the value of the technology (coeff. = -.040, p = .022 in *BUs Directly Affected Sample*; coeff. = .021, p = .001 in *BUs Indirectly Affected*

[12] We estimate regressions that test the effect of the interaction between a firm's patent stock and the tariff cut on the firm's market-to-book value. These regressions are estimated on single-segment firms and for every two-digit SIC code. The regression models take the following form:

$$MktBook_{j,t} = \alpha_t + \beta_1 \times T.Cut_t + \beta_2 \times N.Patents_{j,t} + \beta_3 \times T.Cut_t \times N.Patents_{j,t},$$

where $N.Patents_{j,t}$ is the logarithm of the total number of patents granted in a five-year window, and $T.Cut_t$ is a dummy variable, equal to 1 in the years following the tariff cut. Each regression is estimated over 10 years (5 before to 5 after the tariff cut) and includes control variables (log of assets, the ratio of EBIT over sales, and ratio of CAPEX over sales), firm fixed-effects, and clustered standard errors at the firm level. We estimate the regressions at the two-digit SIC level. In many cases, the sample size of each regression would be too small to obtain reliable estimates at four- and three-digit SIC levels. Because we match observations at the two-digit SIC level, estimating the effect of competition on the value of technology at the two-digit SIC level also increases the comparability between treated and matched observation. If the coefficient of β_3 is positive (negative), tariff cuts increase (decrease) the value of technology as a competitive resource. The detailed, descriptive statistics for all samples are available on request.

Sample). That is, if the BU affected by the tariff cut operates in a sector in which competition increases the value of technology and its technological relatedness is equal to the median value of the *BUs Directly Affected Sample*, resource allocations to this BU will decrease by 1.3 percent of segment assets, while those to the firm's other BUs will increase by .7 percent of segment assets.

*********************Please insert Table 4 about here**********************

Robustness Checks

Methodology

We control for whether the results are affected by the matching technique used for the sample formation with a series of tests. With firm-level matches, instead of BU-level matches, we connect treated firms, subject to a tariff cut in one operating product market, with control firms that are unaffected by tariff cuts. We thus we form a single sample of organizations to test both the inflow and outflow of resources at the BU level. The results of this robustness check are qualitatively equivalent to those reported in the paper.

We repeat the main analyses using propensity score matching to find control samples based on the same matching covariates. The results are virtually unchanged. We follow Gormley and Matsa (2011) and repeat the analysis by matching on relative-to-industry median covariates. Again, the results do not change. In placebo tests, in which we sort samples into treated and control observations in years t – 3 and t – 4, we uncover no results, as expected. Finally, we test for the sensitivity of our results to the three-year window for estimating changes in resource allocations; windows of one and five years produce consistent findings. The results and details of all these analyses are available on request.

Dependent Variable

We test for whether firms react to tariff cuts by increasing investment in the BUs affected through the use of alternative proxies. In particular, we test the effect of tariff cuts on the investment component of a BU's operating expenses and on its R&D expenses (data on R&D is available only for 5% of the BUs in our sample). For the first proxy, we adopt an econometric solution that separates the investment component from operating expenses that reflect the amount of goods sold. A BU's cost of goods sold directly depends on its level of sales, but many expenses that could be classified as investments (e.g., R&D, advertising, software, human capital) do not. Accordingly our dependent variable, which we call *Operating Investment*, is the residual obtained from a regression of the BU's sales over operating costs, with the intuition that the residuals of a regression in which operating costs are the dependent variable and sales are the independent variable capture expenses that do not vary with sales and instead fall under greater managerial control. We find evidence of a positive effect of tariff cuts on both *Operating Investment* and *R&D Expenses*; the shock increases the level of investments in affected BUs. Also in this case, the detailed analyses are available on request.

Does Redeployment Create Value?

As stated in the theory section, a fundamental assumption of redeployment theory is profit-maximizing behavior at the corporate level. To confirm this assumption, we assess the impact of resource reallocations in response to tariff shocks on overall firm performance. As measures of performance, we follow the diversification literature and compute the firm's market-to-book value and market-to-sales value (Berger and Ofek, 1995; Lang and Stulz 1994). For our purposes, market measures of performance are better than accounting measures, because they are forward looking. It could take several years for the consequences of a change in corporate investment policy to be reflected in the firm's income statement. The initial impact of investments on accounting returns also may be negative if investment expenses are not capitalized. The firm's market-to-book value is the ratio between the market value of the firm and the book value of its assets; its market-to-sales value is the ratio between the market value of the firm and its total sales. The firm's market value equals the sum of its market capitalization and the book value of the firm's debts. Again, as with our measure of resource reallocation, we note the change in performance caused by our treatment. Therefore, the dependent variables reflect the difference between the average values of the multiples in the three years after the tariff cut minus the average value of the multiples in the three years before it[13]. The independent variables are a dummy that identifies treated versus control firms, the amount of cash transfer (positive or negative) received by the BU subject to the tariff cut, and the interaction of these variables; we also include the standard controls. The sample size (1,372 observations) is smaller than that of the *BUs Directly Affected Sample* because some diversified firms lack valid data in COMPUSTAT to enable us to calculate their market multiples. To keep the sample balanced when a firm lacks these data, we delete its corresponding matched observation too.

*********************Please insert Table 5 about here**********************

Table 5 displays the results. In both models, the interaction of the tariff cut dummy with the resource allocation received by the BUs subject to the shock has a positive coefficient (market-to-book coeff. = .466, p = .000; market-to-sales coeff. = 1.721; p = .051). These findings support the idea that we observe value-creating activity. As we noted, a tariff cut produces an average increase in resource allocation of 3.4 percent of the segment assets, which in turn would produce a 1.6 percent gain in the market-to-book value and a 5.9 percent gain in the market-to-sales value, relative to a scenario in which the increase in allocation happens under normal market conditions.

Finally, the main effect of the resource transfer is always negative with a low p-value, but if we analyze it together with the interaction, the picture becomes richer. That is, in the absence of a trade shock, the average impact of resource transfers is negative, consistent with predictions

[13] Models testing the effect of redeployment on value creation might be subject to endogeneity concerns as long as past performance is correlated with both future performance and to the availability of resources for reallocation. To address such concerns our matching methodology already ensures that treatment and control firms have a similar amount of resources available for reallocation. Furthermore, we use as dependent variable the delta in performance between the pre- and post-shock period which is equivalent to including past performance as a control.

of a dark side of internal capital markets (Ozbas and Scharfstein, 2010; Scharfstein and Stein, 2000). However, when one of a firm's BUs suffers a strong negative competitive shock, such as the one we examine, the net impact of resource transfers on firm performance becomes positive if we use the coefficients of the market-to-sales regression (1.721 > 1.575) and is eight times lower in the regression with market-to-book value as dependent variable (-.529 + .466 = -.063).

Evidence from a Scenario Experiment

The central argument of this paper is that competitive shocks do not have the same effects on resource redeployment as demand ones.

Our evidence so far is based on the statistical analysis of firm-level aggregated data. At the micro level however, decisions about resource redeployment are rooted in managerial behavior and in managerial perception of problems. A confirmation test of our theory would thus examine managerial allocation decisions in reaction to both demand and competitive shocks. The benefit of studying how individuals allocate capital in a simplified setting is that it allows us to exert greater control, holding firm and environmental characteristics constant, and manipulating only the core variables of interest.

*********************Please insert Table 6 and 7 about here**********************

We base this additional test on Bardolet et al. (2011). In particular, we asked each participant in two groups of finance-trained MBA students, to take the role of the top manager in charge of capital allocation in a hypothetical international consumer product company with three main product divisions (Home Care, Beauty Care, and Health Care). The experiment had two stages and two treatments (demand and competition); it was administered in class through the Qualtrics platform. In the first stage we asked the participants in the two groups to allocate the 15 USD millions of the investment budget for the year 2020 to the three operating BUs of our hypothetical firm, based on the same brief business description and summary financial information for the year 2019. The upper part of Table 6 contains the summary financial information that was shown to participants. In the second stage, after the participants decided on an initial allocation, it was reported that new information was made available in the form of a sector report from the firm's management consultants. The first group of MBA students was told that the Beauty Care market was subject to a high threat of new entrants, while the competitive conditions in the Health Care and Home Care Market appeared stable. In a similar fashion, the second group of MBA students was told that demand in the Beauty Care market was declining while this was not the case in the two remaining BUs. Both groups were provided with an updated version of the initial table containing information about their respective treatment (lower part Table 6). We thus asked participants if they would want to reconsider their initial allocation decision in light of the new information. Under both treatments we avoided providing any information about the potential effect of addition investment in the Beauty Care division, i.e. no assumption was introduced on the marginal returns.

Table 7 contains the results of the allocation decisions made by the participants. We obtained 37 answers to the competition survey (32 valid) and 40 answers to the demand survey (35 valid). We eliminated 5 answers from each survey after asking a question testing the participant understanding of the treatment. The first evidence is that participants' allocation decisions in the first stage of the task are very similar across the two groups. For example, 4.82 USD millions were on average allocated to the Beauty Care division in the competition survey, 4.76 in the demand survey. Interestingly, resource allocations appear to be negatively related to the size of the division. In the pre-treatment scenarios participants gave their preference to the Health Care, Beauty Care, and Home Care divisions in the order. This behavior likely reflects some underlying belief about potential growth and long-term profitability of these businesses.

A quick comparison of the pre- and post-treatment allocations decisions in the two scenarios supports for the idea that competitive shocks and demands shocks are framed differently in the mind of managers. Resource allocation to the Beauty Care division on average increased by 1.09 (two tailed *p-value* of the difference = 0.006) in the competition scenario. Consequently, resource allocation to the Health Care division decrease by 0.79 (p = 0.018) and resource allocation to the Home Care division decreased by 0.29 (p = 0.196). Vice-versa, resource allocation to the Beauty Care division in the demand scenario decreased by 1.38 (p = 0.002). Resource allocation to the Health Care division increased by 0.50 (p = 0.119) and resource allocation to the Home Care division increased by 0.89 (p = 0.001).

DISCUSSION AND CONCLUSIONS

This article examines the effect of increases in competition following trade shocks on the redistribution of non-scale free resources within diversified firms. We draw on a sample from manufacturing industries for the period 1976–2006, including 799 BUs affected by tariff cuts, and 1,247 BUs indirectly affected by tariff cuts because they belong to companies with an affected BU, both matched with control groups of equal size. The difference between capital expenditures and cash flow provides a proxy that captures non-scale free resource reallocations. Our results complement findings from literature pertaining to diversification, performance, and firm resources (Helfat and Eisenhardt, 2004; Levinthal and Wu, 2010; Lieberman *et al.*, 2017; Sakhartov and Folta, 2014; Wu, 2013) by revealing a positive, significant effect of competitive threats on resource reallocations toward BUs affected by the shock, a positive moderation of sunk cost, and a negative moderation of technological synergies on resource redeployment.

Our findings about the moderating effects of sunk costs confirm the importance of an opportunity cost logic in determining resource allocation choices after a competitive shock. The more a firm has sunk assets into a sector affected by a shock, the more credible its threat to move cash to this BU, and thus the more attractive the fight option is, compared with a flight option. These results are consistent with Lieberman *et al.* (2017) and with economic theory pertaining to sunk costs and hysteresis (Dixit, 1989, 1992).

Our findings regarding the interaction between technological synergies and resource redeployment also support the view that these two mechanisms of value creation are interdependent (Lieberman *et al.*, 2017; Sakhartov and Folta, 2014). We find a negative moderation only in sectors in which the tariff cut positively influences the value of technology. In sectors where the opposite happens, this effect is not significant.

This article thus indicates that the direction of resource reallocations critically depends on the type of shock. Prior work has established that the optimal reaction for diversifiers experiencing a decline in demand in one of their product markets is to shift non-scale free resources away from it (Levinthal and Wu, 2010; Lieberman *et al.*, 2017; Wu, 2013). On the contrary, our theoretical framework, focused on competition, relaxes an assumption of Levinthal and Wu's (2010) general model and treats the rate of return for the firm in the sector affected by the competitive shock as contingent on its resource reallocation. This novel view allows us to predict and confirm that diversifiers react to negative competitive shocks by increasing their commitment to the affected product market, consistent with evidence that competition causes firms to invest in differentiation (Aghion *et al.*, 2005; Fernández-Kranz and Santaló, 2010; Flammer, 2015) and that access to internal resources in competitive environments is particularly beneficial for firm performance (Deb *et al.*, 2017; Frésard, 2010).

However, is the reallocation of resources to BUs affected by competition a profit maximizing choice? We test the efficiency assumption and find that reallocating resources to BUs affected by tariff cuts contributes to value creation. It is important to note that our study does not question the results of agency literature involving internal capital markets (Ozbas and Scharfstein, 2010; Scharfstein and Stein, 2000). Rather, we find that, consistent with the presence of agency problems, the main effect of resource reallocation tends to be associated with diminished overall firm performance. However, resource redeployment increases performance after a competitive shock. We regard this point as critical, because the internal market for resources is one of the most important features separating diversified firms from single-segment competitors (Williamson, 1975). In turn, we posit that it may be possible to reconcile mixed results regarding the link between diversification and performance (Berger and Ofek, 1995; Santaló and Becerra, 2008; Villalonga, 2004a, 2004b), by looking more deeply into strategic motivations for resource redeployment. As our findings show, an important part of diversifiers' advantage resides in their reallocation processes, not just resource synergies (Berger and Ofek, 1995; Markides and Williamson, 1996; Teece, 1982; Villalonga, 2004a, 2004b). More precisely, the reallocation of non-scale free resources in internal markets is a value creation mechanism for diversified firms, under the distinct contingencies that we highlight.

Our findings also may be of interest for studies of competitive dynamics (Smith, Ferrier, and Ndofor, 2001). Diversified firms internally transfer resources across their operating sectors, so exogenous increases in competition in sectors populated by diversified firms could generate stronger competitive reactions from incumbents. Sectors that are not directly affected instead could experience less competitive pressure, due to the decreased resource allocation to BUs operating in stable market conditions. This deduction has important policy implications for diversifiers with dominant positions in different markets; a competitive shock in one market could spill over to another solely because these markets are within the portfolio of the same (dominant) company. Thus, antitrust experts should note that the antecedents of competitive pressures could be more endogenous than expected.

We also acknowledge that our study suffers some limitations. First, our empirical test of non-scale free resource reallocations is limited to financial resources. Although we believe our results likely generalize to other fungible categories of non-scale free resources, we are unable to consider them explicitly in our empirical analysis. Second, our tests of the effect of sunk costs and scale free resource relatedness use proxies developed with secondary accounting or patent data. As a result, our measures may contain some measurement error. This concern, by itself, should only affect the difficulty of confirming the hypotheses as long as the proxies are not biased. Nevertheless, researchers with access to detailed data at the level of the firm or BU could helpfully test the robustness of our results. Third, we exclude agency explanations for internal resource transfers, as outside the scope of our research. Continued studies of the effects of compensation, firm structural elements, or internal power struggles on resource reallocations would enrich insights into how diversified firms allocate resources (Rajan, Servaes, and Zingales, 2000).

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Figure 1: Tariff cut events by year

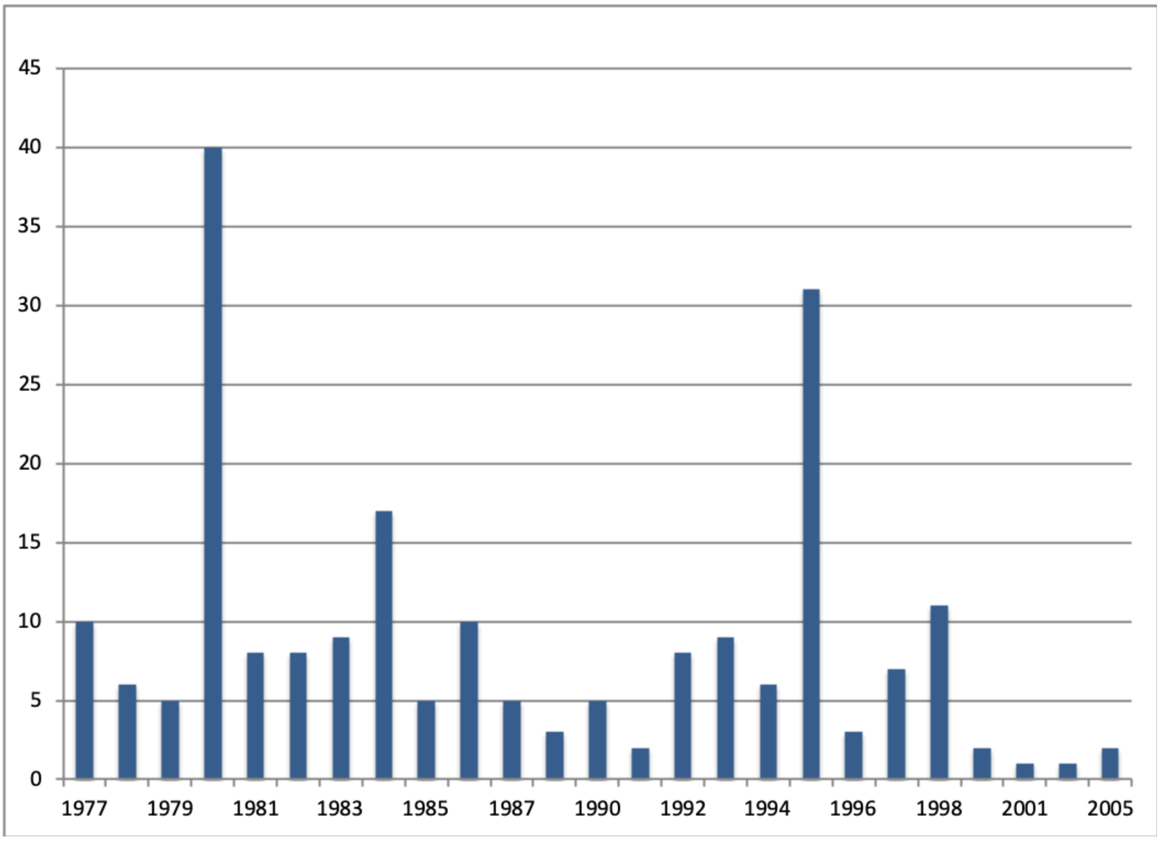
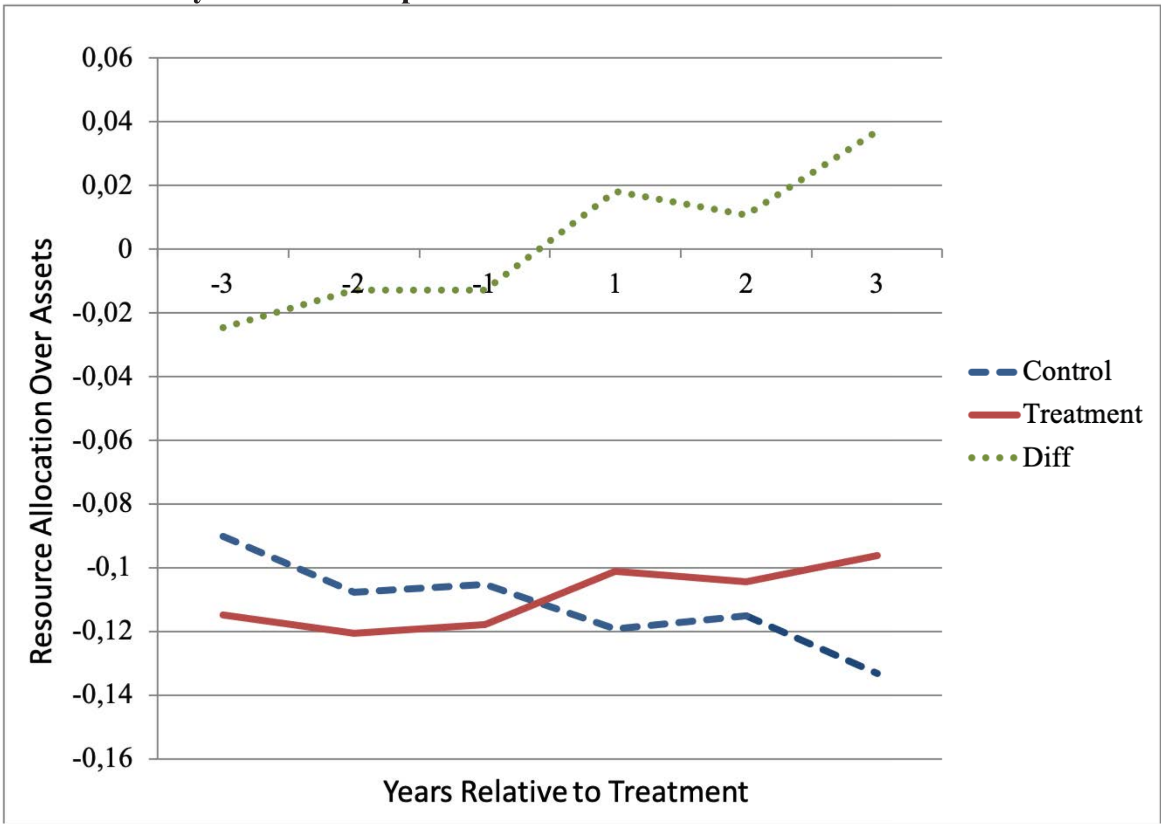


Figure 2: Trends in resource allocations over assets

a. BUs Directly Affected Sample



b. BUs Indirectly Affected Sample

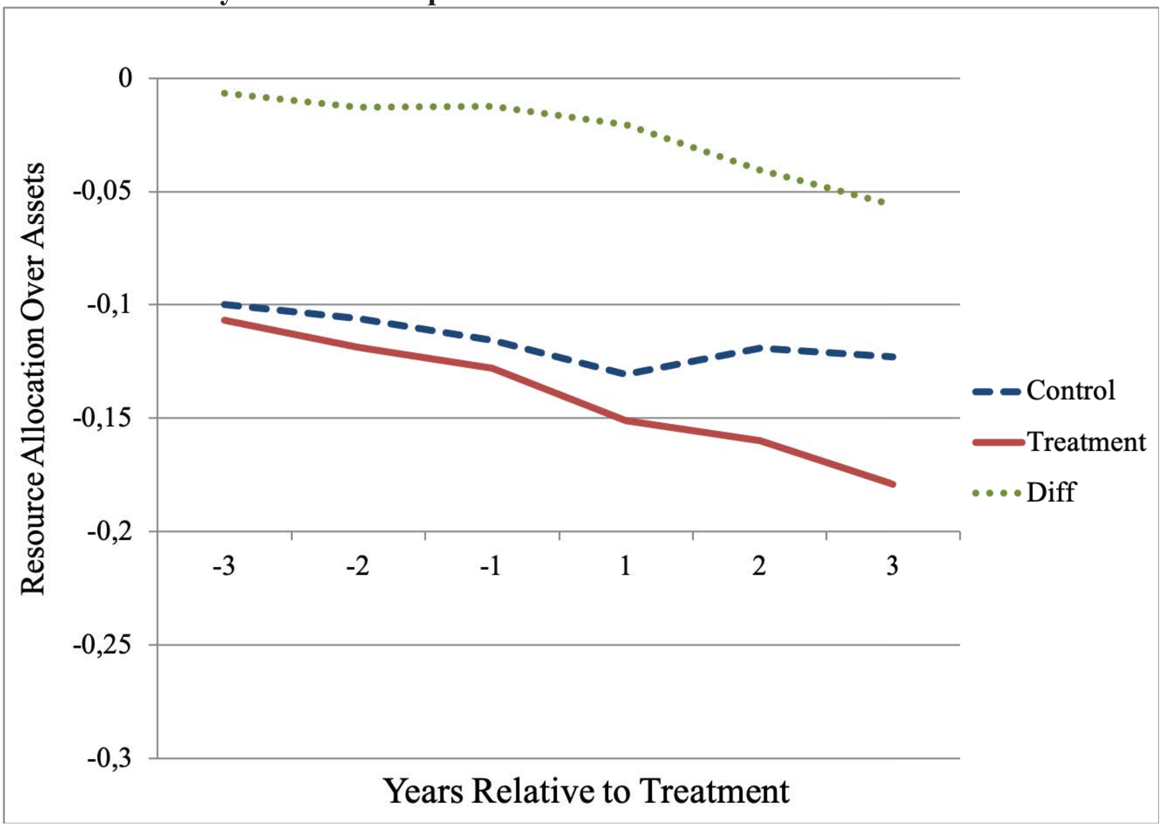


Figure 3: Total effect of tariff cut on resource allocation at different levels of sunk costs

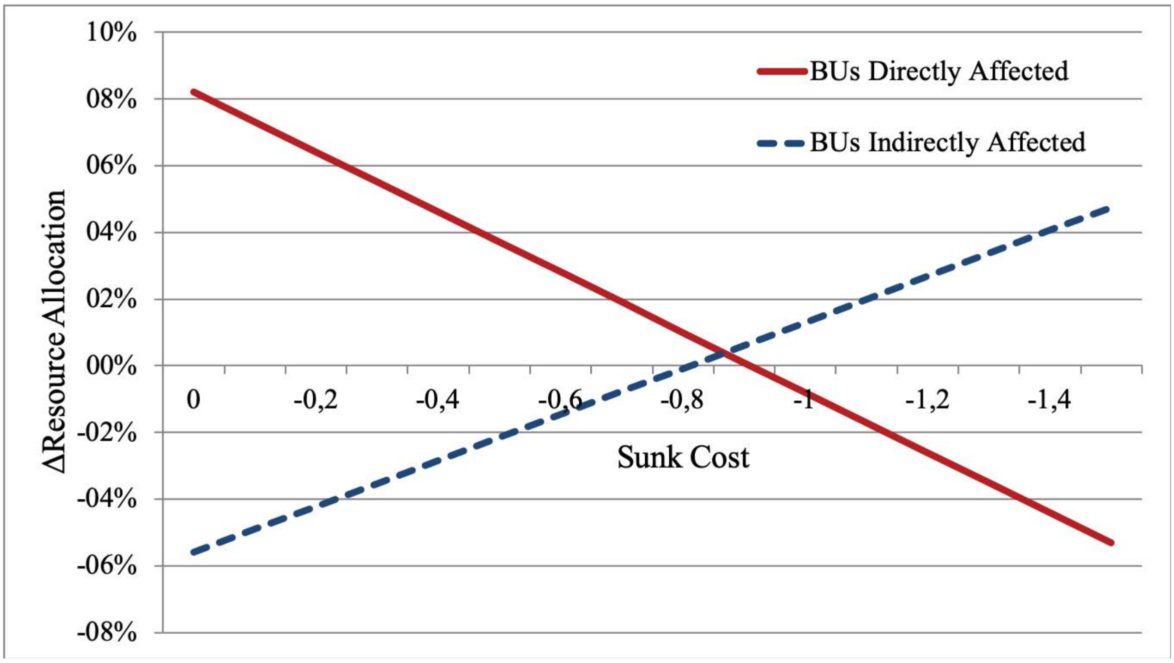


Table 1: Sample descriptive statistics

a. BUs Directly Affected Sample

		N. Obs.	Mean	Min	Max	SD	25p	50p	75p
Matching variables									
Resource Allocation	Treatment	799	-0.11	-6.65	1.18	0.34	-0.17	-0.09	-0.02
	Control	799	-0.10	-1.34	0.95	0.15	-0.15	-0.09	-0.03
BU Sales (log)	Treatment	799	4.22	0.09	10.08	1.98	2.70	4.33	5.61
	Control	799	4.31	0.12	9.48	1.90	2.96	4.37	5.61
Firm Sales (log)	Treatment	799	5.51	0.91	10.99	2.04	3.92	5.56	7.16
	Control	799	5.53	0.86	10.97	1.96	4.00	5.56	6.95
Firm Cash (log)	Treatment	799	2.69	0.00	9.65	1.85	1.21	2.42	4.08
	Control	799	2.68	0.00	9.69	1.78	1.19	2.47	3.88
Firm Leverage	Treatment	799	0.56	0.08	2.26	0.21	0.44	0.55	0.65
	Control	799	0.55	0.10	1.42	0.17	0.44	0.54	0.63
Number of BUs	Treatment	799	3.31	2.00	10.00	1.35	2.00	3.00	4.00
	Control	799	3.21	2.00	10.00	1.24	2.00	3.00	4.00
Independent Variables and Controls									
Sunk Cost	Treatment	799	-0.53	-2.17	0.00	0.41	-0.67	-0.43	-0.24
	Control	799	-0.55	-2.06	0.00	0.41	-0.69	-0.44	-0.26
Tech. Relatedness	Treatment	799	1.08	0.00	8.12	1.50	0.00	0.33	1.77
	Control	799	1.07	0.00	7.83	1.55	0.00	0.27	1.64
Primary Sic	Treatment	799	0.18	0.00	1.00	0.38	0.00	0.00	0.00
	Control	799	0.19	0.00	1.00	0.39	0.00	0.00	0.00
Credit Rating	Treatment	799	0.16	0.00	1.00	0.37	0.00	0.00	0.00
	Control	799	0.15	0.00	1.00	0.36	0.00	0.00	0.00
Number of Analysts	Treatment	799	4.19	0.00	39.00	7.27	0.00	0.00	6.00
	Control	799	4.99	0.00	39.00	8.33	0.00	0.00	7.00
Disclose Advertising	Treatment	799	799	0.39	0.00	1.00	0.49	0.00	0.00
	Control	799	0.39	0.00	1.00	0.49	0.00	0.00	1.00
Disclose R&D	Treatment	799	0.39	0.00	1.00	0.49	0.00	0.00	1.00
	Control	799	0.65	0.00	1.00	0.48	0.00	1.00	1.00
Δ MKT Size	Treatment	799	0.59	-0.95	17.28	1.44	-0.10	0.31	0.78
	Control	799	6.48	-0.98	4650.47	164.53	-0.14	0.35	0.76
Δ MKT Uncertainty	Treatment	799	-0.01	-0.23	0.39	0.05	-0.03	-0.01	0.00
	Control	799	-0.01	-0.24	0.25	0.03	-0.02	0.00	0.01
% Primary Segment	Treatment	799	0.16	0.00	0.63	0.16	0.00	0.16	0.28
	Control	799	0.16	0.00	0.67	0.17	0.00	0.13	0.28
% Diversified	Treatment	799	0.67	0.14	1.00	0.23	0.55	0.69	0.87
	Control	799	0.69	0.07	1.00	0.22	0.58	0.72	0.85
Market Size (log)	Treatment	799	7.80	0.75	11.82	1.52	6.88	7.84	8.73
	Control	799	7.85	0.12	12.84	1.65	6.86	7.92	8.89
Market ROA	Treatment	799	0.15	-0.04	1.14	0.08	0.10	0.14	0.17
	Control	799	0.14	-1.59	0.95	0.10	0.10	0.14	0.18
Mkt. Concentration	Treatment	799	0.26	0.04	1.00	0.19	0.13	0.21	0.31
	Control	799	0.25	0.04	1.00	0.20	0.12	0.18	0.32
PERFORMANCE ANALYSIS SAMPLE									
Market-to-Book	Treatment	686	1.06	0.17	7.75	0.74	0.64	0.84	1.25
	Control	686	1.08	0.08	19.37	1.08	0.65	0.83	1.22
Market-to-Sales	Treatment	686	1.00	0.07	20.55	1.33	0.43	0.67	1.10
	Control	686	1.06	0.08	44.11	2.29	0.46	0.67	1.08

b. BUs Indirectly Affected Sample

		N. Obs.	Mean	Min	Max	SD	25p	50p	75p
Matching variables									
Resource Allocation	Treatment	1247	-0.10	-2.50	4.44	0.22	-0.17	-0.09	-0.03
	Control	1247	-0.10	-1.77	0.87	0.14	-0.15	-0.09	-0.03
BU Sales (log)	Treatment	1247	4.63	0.06	10.91	2.00	3.15	4.72	6.01
	Control	1247	4.58	0.13	10.37	1.87	3.17	4.64	5.84
Firm Sales (log)	Treatment	1247	6.03	0.91	10.99	2.06	4.67	6.19	7.46
	Control	1247	5.86	0.45	10.65	1.91	4.41	6.09	7.27
Firm Cash (log)	Treatment	1247	3.08	0.00	9.65	1.97	1.49	2.99	4.37
	Control	1247	2.88	0.00	8.87	1.78	1.43	2.79	4.15
Firm Leverage	Treatment	1247	0.57	0.12	2.50	0.21	0.45	0.55	0.65
	Control	1247	0.56	0.13	1.73	0.17	0.45	0.55	0.64
Number of BUs	Treatment	1247	3.90	2.00	10.00	1.54	3.00	4.00	5.00
	Control	1247	3.57	2.00	10.00	1.34	3.00	3.00	4.00
Independent Variables and Controls									
Sunk Cost	Treatment	1247	-0.57	-2.17	0.00	0.44	-0.67	-0.45	-0.27
	Control	1247	-0.55	-2.53	0.00	0.44	-0.68	-0.45	-0.25
Tech. Relatedness	Treatment	1247	1.23	0.00	8.12	1.56	0.02	0.57	1.95
	Control	1247	0.89	0.00	7.69	1.42	0.00	0.16	1.25
Primary Sic	Treatment	1247	0.14	0.00	1.00	0.35	0.00	0.00	0.00
	Control	1247	0.17	0.00	1.00	0.38	0.00	0.00	0.00
Credit Rating	Treatment	1247	0.18	0.00	1.00	0.39	0.00	0.00	0.00
	Control	1247	0.16	0.00	1.00	0.37	0.00	0.00	0.00
Number of Analysts	Treatment	1247	4.63	0.00	40.00	7.68	0.00	0.00	7.00
	Control	1247	4.93	0.00	50.00	7.90	0.00	1.00	7.00
Disclose Advertising	Treatment	1247	0.39	0.00	1.00	0.49	0.00	0.00	1.00
	Control	1247	0.38	0.00	1.00	0.49	0.00	0.00	1.00
Disclose R&D	Treatment	1247	0.71	0.00	1.00	0.46	0.00	1.00	1.00
	Control	1247	0.66	0.00	1.00	0.48	0.00	1.00	1.00
Δ MKT Size	Treatment	1247	1.17	-0.98	827.79	23.47	-0.12	0.26	0.76
	Control	1247	0.55	-0.99	29.28	1.61	-0.09	0.31	0.76
Δ MKT Uncertainty	Treatment	1247	-0.01	-0.24	0.17	0.03	-0.02	-0.01	0.01
	Control	1247	-0.01	-0.22	0.41	0.04	-0.02	0.00	0.01
% Primary Segment	Treatment	1247	0.16	0.00	1.00	0.18	0.00	0.13	0.30
	Control	1247	0.16	0.00	0.83	0.17	0.00	0.13	0.29
% Diversified	Treatment	1247	0.71	0.08	1.00	0.21	0.59	0.74	0.87
	Control	1247	0.71	0.07	1.00	0.21	0.59	0.74	0.87
Market Size (log)	Treatment	1247	8.01	0.99	13.06	1.72	6.86	7.99	9.21
	Control	1247	7.92	2.51	13.22	1.71	6.70	7.92	9.10
Market ROA	Treatment	1247	0.15	-0.06	0.59	0.07	0.10	0.14	0.18
	Control	1247	0.14	-0.10	0.48	0.07	0.10	0.14	0.18
Mkt. Concentration	Treatment	1247	0.26	0.04	1.00	0.20	0.12	0.19	0.34
	Control	1247	0.26	0.04	1.00	0.20	0.12	0.20	0.36

Table 2: Correlations

Notes: The bottom left triangle contains the pairwise correlations across independent and control variables calculated on the *BUs Directly Affected Sample*. The upper right triangle contains the pairwise correlations calculated on the *BUs Indirectly Affected Sample*.

UPPER RIGHT: BUS INDIRECTLY AFFECTED SAMPLE

BOTTOM LEFT: BUS DIRECTLY AFFECTED SAMPLE

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1	Tariff Cut		-0.01	0.01	0.04	0.05	0.11	0.02	-0.02	0.11	-0.05	0.03	-0.02	0.01	0.05	0.02	0.00	0.01	0.00	0.03	0.02	-0.01
2	Resource Allocation	-0.02		0.01	0.04	0.02	0.02	0.07	-0.03	0.05	-0.02	0.03	-0.02	-0.03	-0.04	0.02	-0.01	0.02	-0.06	0.05	-0.19	-0.05
3	BU Sales	-0.03	-0.01		0.92	0.82	0.31	0.12	-0.63	0.42	0.09	0.44	0.41	0.03	0.23	-0.04	-0.04	0.14	-0.02	0.40	-0.08	-0.02
4	Firm Sales	-0.01	0.04	0.91		0.88	0.48	0.13	-0.65	0.40	-0.04	0.43	0.43	0.03	0.22	-0.03	-0.03	0.06	0.03	0.33	-0.07	0.00
5	Firm Cash	0.00	0.01	0.79	0.87		0.43	0.03	-0.63	0.43	-0.03	0.43	0.40	0.04	0.25	-0.02	-0.06	0.08	-0.05	0.34	-0.06	0.00
6	Number of Bus	0.04	0.02	0.25	0.42	0.40		0.12	-0.13	-0.03	-0.16	0.08	0.11	0.08	0.05	0.00	0.04	-0.08	0.17	0.03	-0.02	0.02
7	Firm Leverage	0.04	0.08	0.07	0.09	-0.01	0.09		-0.17	0.05	-0.03	0.22	-0.04	-0.08	-0.04	-0.01	0.00	-0.02	0.00	0.05	-0.10	0.01
8	Sunk Cost	0.02	-0.03	-0.73	-0.66	-0.62	-0.05	-0.11		-0.50	0.02	-0.61	-0.30	0.11	-0.16	0.02	0.16	-0.08	0.25	-0.33	0.13	-0.03
9	Tech Relatedness	0.00	-0.04	0.42	0.38	0.42	-0.07	0.00	-0.50		0.09	0.37	0.28	-0.03	0.29	-0.02	-0.11	0.17	-0.28	0.41	-0.09	-0.12
10	Primary Sic	-0.01	0.01	0.05	-0.11	-0.10	-0.20	0.00	-0.07	0.11		0.01	0.02	0.01	0.00	-0.01	-0.02	0.45	-0.18	0.23	-0.05	-0.18
11	Credit Rating	0.02	0.00	0.42	0.42	0.41	0.05	0.24	-0.57	0.36	0.03		0.22	-0.09	0.11	-0.01	-0.14	0.07	-0.20	0.25	-0.09	0.02
12	Number of Analysts	-0.05	-0.02	0.46	0.48	0.47	0.13	-0.09	-0.33	0.34	-0.02	0.21		0.04	0.14	-0.02	-0.02	0.02	0.01	0.18	0.03	-0.01
13	Disclose Advertising	0.00	-0.05	0.02	0.01	0.05	0.06	-0.04	0.10	-0.04	-0.03	-0.05	0.06		0.09	-0.02	0.06	0.01	0.04	-0.06	0.14	0.03
14	Disclose R&D	-0.01	-0.01	0.21	0.21	0.22	0.03	-0.02	-0.17	0.31	-0.03	0.11	0.15	0.07		-0.03	-0.03	0.04	-0.12	0.13	-0.05	-0.04
15	Δ MKT Size	-0.03	0.03	-0.06	-0.04	-0.03	0.03	-0.04	0.02	-0.02	-0.01	-0.01	-0.02	-0.02	-0.03		0.00	-0.02	0.02	-0.10	-0.06	0.08
16	Δ MKT Uncertainty	-0.07	-0.02	0.00	0.03	0.04	0.09	0.07	0.04	-0.15	-0.09	0.01	0.01	0.12	-0.04	0.00		-0.02	0.20	-0.14	0.11	0.04
17	% Primary Segment	0.01	-0.04	0.02	-0.05	-0.01	-0.12	-0.05	-0.02	0.19	0.47	0.03	-0.02	0.05	0.04	-0.03	-0.10		-0.32	0.52	-0.05	-0.37
18	% Diversified	-0.03	-0.01	0.07	0.10	0.02	0.22	0.05	0.16	-0.31	-0.19	-0.15	0.04	0.05	-0.12	0.04	0.16	-0.33		-0.30	0.17	0.27
19	Market Size	-0.02	0.01	0.33	0.29	0.30	-0.01	0.01	-0.37	0.51	0.24	0.20	0.17	-0.09	0.14	-0.13	-0.21	0.38	-0.29		-0.12	-0.52
20	Market ROA	0.04	-0.15	0.01	-0.01	0.00	-0.02	-0.04	0.08	-0.08	-0.04	-0.06	0.05	0.12	-0.03	-0.49	0.10	-0.04	0.15	-0.06		0.09
21	Market Concentration	0.01	0.00	0.05	0.05	0.04	0.01	0.06	-0.10	-0.14	-0.20	0.06	0.03	-0.01	-0.07	0.10	0.10	-0.36	0.27	-0.50	0.05	

Table 3: Main results

Notes: This table contains the results of regression analyses performed on the sample of BUs directly affected by a tariff cut in their operating product market (*BUs Directly Affected Sample*) and on the sample of BUs belonging to firms affected by tariff cuts but that did not directly experience these events in their operating product markets (*BUs Indirectly Affected Sample*). Both groups of BUs are matched with corresponding control BUs belonging to diversified firms that are not affected by tariff cuts. See the Method section. For the treated group in the *BUs Indirectly Affected Sample*, the values of *Sunk Cost* and *Technological Relatedness* that we test in the analyses are those of the BU experiencing the tariff cut. For the control group in the same sample, we use the values of the most similar BU to the one experiencing the tariff cut in the matched treated firm. Exact *p*-values are in parentheses.

Dependent Variable: ΔResource Allocation	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
	BUs Directly Affected Sample				BUs Indirectly Affected Sample			
Tariff Cut	0.034	0.079	0.023	0.077	-0.017	-0.055	-0.031	-0.055
	(0.031)	(0.028)	(0.055)	(0.020)	(0.057)	(0.001)	(0.021)	(0.002)
Sunk Cost		0.064		0.050		0.000		0.001
		(0.066)		(0.190)		(0.996)		(0.983)
T. Cut X Sunk Cost		0.086		0.145		-0.069		-0.063
		(0.039)		(0.053)		(0.002)		(0.019)
Technological Relatedness			0.005	-0.003			-0.000	0.003
			(0.592)	(0.754)			(0.976)	(0.528)
T. Cut X Tech. Relatedness			0.010	0.031			0.012	0.002
			(0.477)	(0.161)			(0.022)	(0.715)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
N	1598	1598	1598	1598	2494	2494	2494	2494
Adj. R-sq	0.003	0.004	0.002	0.006	0.014	0.017	0.015	0.017

Table 4: Effects of scale free resource relatedness on resource reallocation depending on whether tariff cuts increase or decrease the value of technology

Notes: This table separates industries in which tariff cuts had a positive effect on the value of technology from industries in which the opposite occurred. For each type of industry, we form a *BUs Directly Affected Sample* and a *BUs Indirectly Affected Sample* using the matching procedure described in the Method section. A description of the control variables and the procedure for their calculation also appear in the Method section. For the treated group in the *BUs Indirectly Affected Sample*, the values of *Sunk Cost* and *Technological Relatedness* that we test are those of the BU experiencing the tariff cut. For the control group in the same sample, we use the values of the most similar BU to the one experiencing the tariff cut in the matched treated firm. Exact *p*-values are in parentheses.

Dependent Variable: ΔResource Allocation	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
	Competition Increases Patent Value				*Competition Decreases Patent Value*			
	BUs Directly Affected		BUs Indirectly Affected		BUs Directly Affected		BUs Indirectly Affected	
Tariff Cut	0.060	0.004	-0.061	-0.052	0.006	0.028	-0.073	-0.120
	(0.100)	(0.743)	(0.000)	(0.005)	(0.731)	(0.434)	(0.004)	(0.000)
Tech. Relatedness	0.009	0.016	-0.004	-0.005	-0.020	-0.022	0.006	0.014
	(0.178)	(0.057)	(0.669)	(0.547)	(0.054)	(0.067)	(0.296)	(0.158)
T. Cut X Tech. Rel.	-0.040	-0.057	0.021	0.025	0.003	0.011	0.016	-0.006
	(0.022)	(0.050)	(0.001)	(0.013)	(0.626)	(0.076)	(0.237)	(0.681)
Sunk Cost		0.088		-0.022		0.094		0.141
		(0.017)		(0.581)		(0.418)		(0.015)
T. Cut X Sunk Cost		-0.144		0.027		0.067		-0.123
		(0.125)		(0.533)		(0.332)		(0.009)
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Control Variables	YES	YES	YES	YES	YES	YES	YES	YES
N. Observations	432	432	746	746	344	344	454	454
Adj. R sq.	0.111	0.116	0.034	0.032	-0.047	-0.048	0.012	0.025

TABLE 5: Performance analysis

Notes: This table contains the results of regression analyses on the subsample of BUs of the *BUs Directly Affected Sample* for which data are available to calculate the market-to-book and market-to-sales values. To keep the sample balanced, if data were missing for one observation, we also deleted the corresponding matched observation. The dependent variable is the difference in the average market multiples in the three years after minus the three years before the tariff cut. A description of the control variables and the procedure for their calculation is available in the Method section. Exact *p*-values are in parentheses.

Dependent Variable	ΔMKT Book Model 1	ΔMKT Sales Model 2
Tariff Cut	0.035	0.176
	(0.483)	(0.068)
ΔResource Allocation	-0.529	-1.575
	(0.000)	(0.077)
T. Cut X ΔResource Allocation	0.466	1.721
	(0.000)	(0.051)
Year Fixed Effects	YES	YES
Control Variables	YES	YES
N. Observations	1372	1372
Adj. R sq.	0.058	0.056

TABLE 6: Experiment setup

Notes: In a two-stage experiment administered in class through the Qualtrics platform, two groups of MBA students at IE Business School were asked to allocate 15 USD millions of financial resources to the BUs of a diversified firm. It was specified that the resources were dedicated to investment and that they were not necessary for the BUs current level of operation. In the first stage of the experiment the participants were exposed to a brief description of the BUs current business and to summary financials for the year 2019. In the second stage, after the participants decided on an initial allocation, it was reported that new information was made available in the form of a sector report from the firm's management consultants. The first group of MBA students was told that the Beauty Care market was subject to a high threat of the entrants, while the competitive conditions in the Health Care and Home Care Market appeared stable. In a similar fashion, the second group of MBA students was told that demand in the Beauty Care market was declining while demand in the two remaining business exhibited moderate growth. We thus asked participants if they would want to reconsider their initial allocation decision in light of the new information. Under both treatments we avoided providing any information about the potential effect of additional investment in the Beauty Care division. We therefore left open the possibility that of the additional investment in the Beauty Care unit generating abnormally positive or substandard returns (as compared to the use of the funds in the remaining divisions).

	Health Care	Beauty Care	Home Care	Firm Total
Financials (amounts in USD thousands)				
Total revenues	83,700	104,200	121,300	309,200
Total assets	32,450	47,500	51,050	131,000
Net income margin	20%	19%	19%	19%
Sector outlook (2nd stage only)				
Threat of new entrants	Low	High	Low	
Forecasted demand	Moderate growth	Declining	Moderate growth	

TABLE 7: Experiment result

Notes: This table contains the allocation decisions made by two groups of MBA students. As described in Table 6, in the first stage of the experiment both samples were asked to allocate 15 USD millions of financial resources for investment to the three BUs of a diversified firm. In this stage we provided solely a brief business description for each BU together with summary financial information for the prior year (Mean-Pre). In the second stage the two groups were told that new sector information was received. The first group was told that competition was likely to increase in the sector of the Beauty Care unit. The second group was told that demand was likely to decline in the sector of the Beauty Care unit. The two groups were thus asked if they wanted to reconsider their initial resource allocation decision (Mean-Post). We only consider valid answers in the calculation of the means and of the p-value of the mean difference. For the purpose we have asked a question testing the participants understanding of the treatment.

	N. answers	Valid answers	Mean-Pre	Mean-Post	p-value difference (2-tailed)
Competition increase					
Home care	37	32	4.508	4.214	0.196
Beauty care	*37*	*32*	*4.820*	*5.910*	*0.006*
Health care	37	32	5.680	4.890	0.018
Demand decline					
Home care	40	35	4.494	5.379	0.001
Beauty care	*40*	*35*	*4.764*	*3.384*	*0.002*
Health care	40	35	5.742	6.237	0.119

APPENDIX

In this appendix we clarify the process through which we form the two samples for our empirical analysis. Consider a Treated Firm like the one depicted in in Figure A.a. The firm has three BUs operating in different product markets: BU A experienced a tariff cut in its product market, the products of foreign competitors are suddenly cheaper, BUs B and C instead experienced no tariff cuts. Our goal is to understand how the Treated Firm reacts to this shock, whether it allocates more resources to A and less to B and C or vice versa. Further, we also want to understand how the characteristics of BU A, the extent to which the investment made in BU A can be considered sunk cost and the degree of technological relatedness between BU A and the remaining two BUs, influence the reallocation decision.

For this purpose we form two samples, the *BUs Directly Affected Sample* and the *BUs Indirectly Affected Sample*. The *BUs Directly Affected Sample* is formed by taking BUs A (and all the likes of BU A) and by matching it with a control observation. The control observation is selected within the universe of BUs belonging to non-treated firms (firms experiencing no tariff cuts), based on the pre-shock similarity with BU A, and following the procedure detailed in the methodology section. The same process is also repeated for the formation of the *BUs Indirectly Affected Sample*. We take BU B and C and we match them with control observations belonging to non-treated firms. In the example in Figure A.a, BU A is matched with BU *x* belonging to Firm I; BU B and C are matched with BU *e* from Firm IV and BU *m* from Firm XI.

With the two samples formed in the way illustrated we can already test the main effect of *Tariff Cut* on *Resource Allocation*. If Hypothesis 1 is confirmed, as consequence of the tariff cut BU A will receive a higher amount of resource allocation relative to its control in the post shock period. Vice versa for BU B and C.

Testing the moderating effect of the characteristics of BU A on reallocation instead requires us to perform a second step of matching on the *BUs Indirectly Affected Sample*. For what concerns the *BUs Directly Affected Sample* in fact, the moderating effect of *Sunk Cost* and *Technological Relatedness* is simply tested by interacting the level of the sunk cost of BU A and BU *x* with the *Tariff Cut* dummy which is 1 for BU A and 0 for BU *x*.

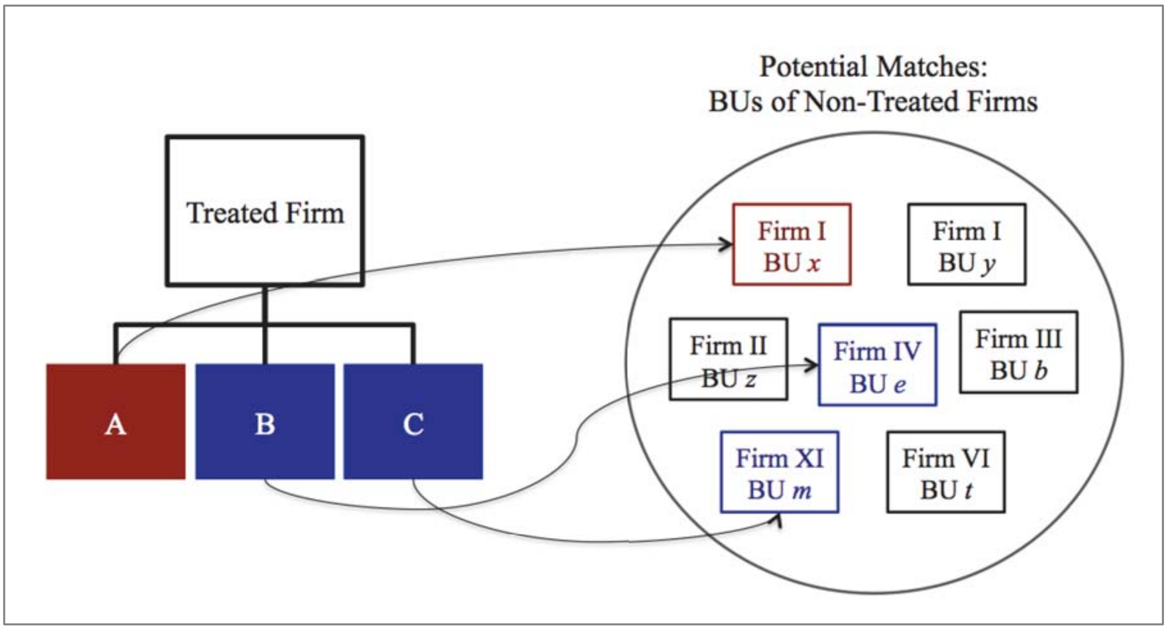
**********************Please insert Figure A about here***********************

To understand why a second step of matching is needed to test the interactions on the *BUs Indirectly Affected Sample* instead, consider the case of BU B depicted in Figure A.b. In the first step we matched BU B with BU *e* from Firm IV. However, our aim in this case is not to test how the characteristics of BU B influence resource allocation to it. Our aim instead is to understand the effect of a within firm relationship on resource allocation to BU B. More precisely, how the *Sunk Cost* and *Technological Relatedness* of the unit affected by the tariff cut (BU A) influence the extent of resources redeployed from BU B. To properly identify the effect of this relationship on the outcome, we thus need to find a counterfactual relationship that is not affected by a tariff cut.

Our solution to this problem involves finding the BU within Firm IV that is the most similar to BU A. Excluding BU *e*, Firm IV has two BUs (BU *f* and *g*) whose relationship with BU *e* could potentially serve as the counterfactual for the relationship between BU A and BU B. To choose between one of the two, we compare the level of pre-shock sales and pre-shock resource allocation of the two candidates with that of BU A. We base our choice on these two variables because we consider them as the best predictors of future levels of resource allocation. In our example the outcome is that we identify BU *g* as the BU most similar to A. In the analysis on the *BUs Indirectly Affected Sample*, we will thus compare the effect that the *Sunk Cost* and *Technological Relatedness* of BU A and BU *g* have on resource allocation to BU B and BU *e* respectively. The online methodological appendix of the paper includes a discussion of how our approach mitigates the potential biases of our identification strategy.

Figure A: Samples formation

a. Matching between the BUs of a Treated Firm and control BUs from Non-Treated Firms



b. Selection of the control firm's most similar BU to the one experiencing the tariff cut