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A bird in the hand is worth two in the bush: Technology search strategies and competition due to import penetration

Raffaele Morandi Stagni[1] | **Andrea Fosfuri**[2] | **Juan Santaló**[3]

[1]Department of Business Administration, Universidad Carlos III de Madrid, Getafe, Madrid, Spain

[2]Department of Management and Technology, Bocconi University, Milan, Italy

[3]Strategy Department, IE Business School/ IE University, Madrid, Spain

Correspondence
Raffaele Morandi Stagni, Department of Business Administration, Universidad Carlos III de Madrid, Calle Madrid 126—6.0.37, 28903 Getafe, Madrid, Spain.
Email: raffaele.morandi@uc3m.es

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Abstract

Research Summary: Do firms respond to tougher competition by searching for completely new technological solutions (exploration), or do they work to defend their position by improving current technologies (exploitation)? Considering the different times to fruition for exploration versus exploitation, in the presence of heightened competition, we argue that firms might not be able to wait for the benefits of technological exploration to materialize. With a panel data set of U.S. manufacturing firms, we show that tougher competition, due to import penetration, leads to a decrease in technological exploration and an increase in technological exploitation. These effects are heterogeneous across industries, firms, and time. To obtain exogenous variation in competition we rely on both instrumental variable regressions and a difference-in-differences design exploiting large changes in import tariffs.

Managerial Summary: A firm's R&D strategy is one of the fundamental determinants of success or failure when responding to competitive threats. In this study, we examine how firms change the knowledge sources used in their R&D efforts in response to substantial increases in import penetration in their domestic market. We find that in the years that immediately follow an increase in import penetration, firms tend to rely more on familiar knowledge in the development of innovations and less on knowledge sources that were not previously used. This switch in R&D strategy also appears to be temporary (reversed in later years), and it is positively associated with an increased likelihood of survival.

KEYWORDS

competition, exploitation, exploration, patents, technology

1 | INTRODUCTION

The search for new knowledge through exploration and the refinement of existing knowledge bases through exploitation are fundamental activities for organizations' adaptive systems, to ensure both short-term performance and long-term survival (March, 1991). Firms engaging in both exploration and exploitation thus might enjoy persistent competitive advantages (He & Wong, 2004; Katila & Ahuja, 2002; Lavie, Kang, & Rosenkopf, 2011). Yet firms also need to adjust their search strategies to the changing characteristics of their external environments, a factor that has attracted substantial attention from management scholars (Luger, Raisch, & Schimmer, 2018; Posen & Levinthal, 2012; Stieglitz, Knudsen, & Becker, 2016). To contribute to this literature stream, we consider the effect of competition on exploration and exploitation in technology development. Our focus on technology reflects both its increasing importance for firm survival and competitive advantage (Schilling, 2002; Teece, Pisano, & Shuen, 1997) and the proximity to March's (1991) original conceptualization of these search strategies. By addressing competition, we highlight an environmental factor that constitutes a primary driver of corporate outcomes (Bernard, Jensen, & Schott, 2006). Specifically, we study competition created by import penetration, which has increased steadily in recent years (Bloom, Draca, & Van Reenen, 2016) to become a central concern for companies (e.g., dealing with imports from China). Strategy scholars have investigated how import competition affects different types of firms' strategies like corporate social responsibility (Flammer, 2015), internationalization (Wiersema & Bowen, 2008), and diversification (Becerra, Markarian, & Santalo, 2020). This article focuses on the impact of import competition on technology search strategies.

Extant research already provides some insights into how firms should adjust their technology search strategies to deal with a heightened competitive environment. Several authors have suggested that firms should consider the type of competition (Polidoro & Theeke, 2012; Toh & Kim, 2013; Toh & Polidoro, 2013). Further, when the required novelty step to respond to increased competitive threats is substantial, firms might need to engage in exploration, even if they deem it riskier and costlier than exploitation (Levinthal & March, 1993; March, 1991). Finally, resources and capabilities can explain firms' heterogeneous responses to environmental threats (e.g., Henderson & Cockburn, 1994).

We propose a theoretical insight that has been overlooked in these prior contributions. That is, we concur that exploration is riskier and costlier than exploitation (He & Wong, 2004; McGrath, 2001), but we highlight that it also requires a longer time horizon to produce results

(March, 1991), due to its slower learning pattern. Competition due to increased import penetration generally results in tight profit margins, low prices, and strong efficiency pressures (Matusik & Hill, 1998; Zahra, 1996). An environmental change in this direction immediately affects firms' bottom lines, in the form of reduced profits and increased bankruptcy risk (Amiti & Konings, 2007; Pavcnik, 2002; Trefler, 2004). Accordingly, companies might be forced to adopt technology search strategies that yield results quickly, before they fail, rather than more aggressive technology search strategies that promise benefits that might materialize farther in the future. All else being equal, this reasoning suggests a positive relationship between increased competition and exploitation and a negative one between increased competition and exploration.

We test the explanatory power of these theoretical arguments among a sample of U.S. manufacturing firms over the years 1989–2006. We adopt two identification strategies to capture the causal link between variations in the competitive environment and firms' technology search strategies.[1] First, we use exchange rates and import tariffs as instruments to estimate the effect of changes in import penetration (Cuñat & Guadalupe, 2009; Xu, 2012) on exploring (*new*) and exploiting (*familiar*) citations in patent applications (e.g., Cao, Gedajlovic, & Zhang, 2009; Katila & Ahuja, 2002). Second, we apply a difference-in-differences (DiD) design with matching, based on large tariff cuts (Flammer, 2015; Frésard, 2010), and thereby test the robustness of our main finding and observe the evolution of firms' responses over time.

The results from the instrumental variable analysis consistently show that after an increase in competitive pressure due to import penetration, organizations tend to focus less on exploration and more on exploitation. In our sample period, an increase in import penetration from 0.15 to 0.2 (i.e. imports end up representing 20% of a sector total sale) produces a 6.3% decrease in the use of new citations in patent applications (exploration) and a 15.8% increase in the repeated usage of citations with which the organization is familiar (exploitation). In a supplementary analysis, we also test the effects of import penetration according to the type of competition and the type of industry affected. We separate imports from low-technology countries (LTCs) from imports from high-technology countries (HTCs). If technological competition has a different effect on search strategies than price-based competition, we might expect the results to differ. Instead, the effects of the two types of import penetration are qualitatively similar. Following Lev, Petrovits, and Radhakrishnan's (2010) we also perform a sample split of industries in which the primary customers are other businesses (B2B) or those in which the primary customers are final consumers (B2C). Consistent with the intuition that import penetration issues a greater threat to firm survival in B2B industries, we find that the effect of import penetration on technological exploration and exploitation is stronger for that group than for B2C industries. Finally, we explore how the relationship between competition and technology search strategies is moderated by firm factors that might alleviate or increase concerns about firm survival (and thus alter the intensity with which future benefits get discounted). The findings show that the negative relationship between competition and exploration is magnified for firms that are relatively more vulnerable, because they have greater degrees of operating leverage and lower degrees of product diversification. Surprisingly though, these factors do not affect the extent of a firm's technological exploitation efforts.

[1]The limited empirical evidence on the relationship between competition and search strategies provides mixed views and suffers from a lack of causal identification (Jansen, Van Den Bosch, & Volberda, 2006; Voss, Sirdeshmukh, & Voss, 2008).

The DiD design confirms the robustness of our main findings when we focus on large competitive shocks (i.e., substantial changes in import penetration): Firms focus less on exploration and more on exploitation. In addition, it offers evidence that firms' responses to competitive shocks are dynamic: In years between $t + 1$ and $t + 3$ (where t is the year of a tariff cut), affected firms reduce their technological exploration (and increase their technological exploitation). This behavior reverses in years $t + 4$ and $t + 5$, when the amount of exploration of treated firms becomes comparable with that of the control group (i.e., not affected by the shock). This evidence implies that firms return to exploration once the competitive conditions in their operating sectors stabilize (Amiti & Konings, 2007; Pavcnik, 2002), which corroborates our theorized mechanism of a decreased risk of failure.

With these findings, this study contributes to two streams of extant literature. First, it informs investigations of the link between search strategies and the environment by showing how increased competitive pressure leads firms initially to focus more on technological exploitation than exploration (Cao et al., 2009; Jansen et al., 2006; Luger et al., 2018; Posen & Levinthal, 2012; Voss et al., 2008). The results support the notion that firms dynamically adjust their technology search strategies to the environmental shifts they face (Luger et al., 2018), and we provide additional evidence that the rate and direction of change in search strategies, due to increased competition, is heterogeneous across industries, firms and time. Second, our results relate to the vast literature stream pertaining to the link between competition and innovation (e.g., Aghion, Bloom, Blundell, Griffith, & Howitt, 2005; Aghion, Harris, Howitt, & Vickers, 2001; Bloom et al., 2016). Many contributions address the *quantity* of innovations produced after a competitive shock, without investigating how competition might affect the *type* of innovations produced, which is the focus of our study. Our findings are in line with Arora, Belenzon, and Patacconi (2018), who consider the evolution of corporate R&D over time and find that companies increasingly abandon basic research (publications) in favor of applied research (patents), and support their conjecture that the shifting composition of R&D is the outcome of increased competitive pressure.

2 | TECHNOLOGY SEARCH STRATEGIES UNDER COMPETITION

Exploration and exploitation are two search strategies with fundamentally different characteristics (March, 1991), which apply to multiple domains of organizational activity and different sets of tasks. We focus on the relationship between competition and exploration/exploitation in *technology* development (i.e., technology search strategies). Exploitation aims to refine the firm's knowledge base, related to existing and familiar technology. It is associated with technological improvements along an established path, which might increase the quality level and/or reduce costs. Exploration instead is the pursuit of novel approaches that might lead to new market opportunities or that radically improve current solutions. It involves distant search, risk-taking, and experimentation with new technologies or areas of knowledge (Manso, 2011).

Some balance between exploration and exploitation is necessary to ensure both short-term performance and long-term survival. Underinvesting in exploitation can lead to insufficient quality or efficiency, which put the company at a competitive disadvantage; underinvesting in exploration instead increases the chance that the firm will suffer from unforeseen paradigmatic changes. A fruitful stream of research offers insights into how organizations achieve a balance between exploration and exploitation, despite the conflicting demands imposed by the two activities (e.g., Gibson & Birkinshaw, 2004; Gupta, Smith, & Shalley, 2006). In particular, a key driver of firms' investments in exploration and exploitation is the external environment. As March (1991: 72) states, "effective selection among forms, routines, or practices is essential to survival, but so also is the generation of new alternative practices, particularly in a changing environment." Understanding the role of the environment thus is essential, and a significant number of studies address the relationship between search strategies and environmental factors (Jansen et al., 2006; Keller & Rady, 1999; Posen & Levinthal, 2012; Voss et al., 2008).

In turn, competitive intensity is an important environmental dimension that firms consider when crafting their strategies (Bowen & Wiersema, 2005). Among the substantial body of empirical research assessing the impact of competition on innovation (e.g., Aghion et al., 2001, 2005; Bloom et al., 2016), current evidence regarding how changes in competitive intensity affect the types of innovation is lagging. We thus focus on changes in competitive intensity brought about by changes in import penetration. Competition due to import penetration has increased steadily in recent decades (Bloom et al., 2016) and has become a major concern for corporations, especially those that face the competitive pressures imposed by imports from China. At an industry level, greater import penetration is conceptually equivalent to an increase in the number of rivals (Matusik & Hill, 1998; Porter, 1981). More competitors in an industry lead to tighter profit margins, lower prices, and strong efficiency pressures (Matusik & Hill, 1998; Zahra, 1996), which may put the firm's very survival at stake (Amiti & Konings, 2007; Pavcnik, 2002; Trefler, 2004). According to Bernard et al. (2006), for a sample of U.S. manufacturing companies, a 10% increase in import penetration is associated with an increased probability of firm death of 12.5%. Pavcnik (2002), studying Chilean trade liberalization, similarly finds that less productive firms are forced out of business.

We argue that an important, generally overlooked, mechanism that links heightened competitive intensity to technology search strategies is the difference in the time to fruition between exploration and exploitation. Both search strategies require upfront investments. However, developing incremental features by modifying current products, services, and processes implies building on accumulated investments within the current knowledge base. Working with novel technologies instead requires more time and investment before reaching profitability (Abernathy & Utterback, 1978; Tushman & Anderson, 1986). Manso (2011) illustrates formally that an optimal incentive scheme that motivates explorative innovation requires substantial tolerance for inferior short-term performance and rewards for long-term success. Notably, technology performance patterns tend to resemble an S-curve (Foster, 1986), such that initial improvements are particularly difficult and expensive to obtain, because the fundamental principles governing technology behavior are poorly understood. The initial performance of new technology in turn tends to be inferior to that of alternative technologies, already present on the market (Foster, 1986). Moreover, new technology likely requires different commercialization patterns, which also need to be explored, tested, and perfected (Manso, 2011). Overall, the learning curve for exploration thus is much slower than that of exploitation (Lieberman, 1987; Schilling, 2002; Schilling, Vidal, Ployhart, & Marangoni, 2003; Spence, 1981). Exploration requires a longer horizon to bear fruit, in addition to entailing higher upfront investments and costs.

However, threats due to increased competitive pressure typically leave firms with little time to respond and adapt to the new environment (Amiti & Konings, 2007; Chang & Xu, 2008). The viability of exploration as a strategy to deal with this sort of environmental change may be limited, because its more distant benefits get discounted at a higher rate, even as the greater upfront costs deplete corporate resources and accelerate organizational demises. According to

Fitzgerald, Balsmeier, Fleming, and Manso (2021), firms that focus on exploitation rather than exploration tend to generate superior short-term operating performance, and Ferreira, Manso, and Silva a. C. (2014) establish a key role of firm tolerance to early failures when they explore new ideas. As Miller and Friesen (1983: p. 223) argue, "extensive risk taking, forceful proactiveness and a strong emphasis on novelty can be very hazardous when competitive or economic conditions are becoming more taxing," so firms operating in competitive environments that engage in higher degrees of exploitation tend to achieve better performance (Jansen et al., 2006).

In summary, because technology exploration takes longer to bear fruit, and time is a key determinant of firm survival in conditions marked by strong rivalry due to import penetration, our main contention states that, *other things equal, firms are more likely to react to increased competition by exploring less and exploiting more*.

3 | EMPIRICS

To investigate the effect of changes in import penetration on the extent to which firms engage in technological exploration and exploitation, we assemble a panel data set of U.S. companies by combining data from different sources. We use the Standard & Poor's Compustat database to obtain information about firms' financials, including operating segments. From the NBER Patent Database (Hall, Jaffe, & Trajtenberg, 2001), we gather information about firms' patent applications, including the citations made and received by firms' patents. We use data from different NBER data sets (Becker, Gray, & Marvakov, 2013; Feenstra, 1996; Feenstra, Romalis, & Schott, 2002; Schott, 2010) to calculate import penetration, our proxy for competition. Finally, we use data about tariffs from the UNCTAD TRAINS data set, provided by the World Bank, and data about exchange rates and consumer price indexes (CPIs) from the international financial statistics of the International Monetary Fund (IMF) to construct instrumental variables.

The resulting data set covers 1991–2006 and is limited to firms with primary operations in manufacturing standard industrial classifications (SIC) 2000–3999, for which trade information is available. This sample period includes years of substantial disruption in terms of trade liberalization, including the ratification of the North American Free Trade Agreement in 1994 and its subsequent implementation. After 2006 and until very recently, trade tariffs applied to major U.S. partners have remained stable. Our choice of sample period also reflects the limited availability of tariff, import, and patent data. That is, the UNCTAD TRAINS database starts in 1989, and we require 2 years of lagged observations for our analyses; the NBER Patent Database and the NBER data necessary to calculate import penetration at the SIC4 level are available only until 2006. We exclude firms that earn less than US$10 million in sales. Our final sample contains 8,480 firm-years in which firms filed at least one patent application and citation data are available; these observations belong to 1,323 firms operating in 107 distinct SIC4 industries.

Our sample has a few limitations that are worth noting. First, we only have data about listed firms, covered by Compustat. Although Compustat data have been used extensively in prior research (e.g., Fitzgerald et al., 2020; Uotila, Maula, Keil, & Zahra, 2009), privately held corporations might react differently to competition, due to their concentrated ownership structure and/or greater tolerance to failure (Ferreira et al., 2014). Second, patenting activity is not distributed uniformly across sectors, which determines the structure of our data. Of the 20 two-digit manufacturing SIC sectors, five are responsible for the lion's share of patenting activity: 28, 35, 36, 37, and 38. These sectors account for 69% of the manufacturing firms present in

Compustat in our study period. Third, we use patents to build measures of exploration and exploitation. However, if firms start exploring more in response to increased import penetration, and also fail more often in achieving a patent, the interpretation of our findings could be problematic. In unreported regressions, we find that the total number of patent applications is unaffected by import penetration, while R&D expenditures decline. These findings are not consistent with firms doing more exploration and obtaining fewer patents.

3.1 | Dependent variables

Our dependent variables for this study are technological exploration and technological exploitation; we use the citations contained in patent applications to reflect these constructs (e.g., Choi, Kumar, & Zambuto, 2016; Katila & Ahuja, 2002; Sorensen & Stuart, 2000). Technological exploration captures the extent to which the firm searches for new knowledge to develop innovations; the measure is the natural logarithm of the total number of new citations contained in patent applications plus 1. A citation is new if it was never used in patent applications filed by the focal firm in the years between t–1 and t–5. Technological exploitation captures the extent to which a firm, in its patent applications, reuses a knowledge base with which it is already familiar. We measure it as the natural logarithm of the total number of times that citations in the focal year were repeatedly used in patent applications filed between $t-1$ and t–5 plus 1. To avoid overinflating the measure, we only count repeated usage of the same citation across different years. Each citation thus can take a value between 1 and 5, depending on whether the citation has been used in just one of the 5 years prior to the focal year or at least once in each of those 5 years.[2]

Our use of separate measures of technological exploration and technological exploitation is purposeful. In general, we agree with Lavie, Stettner, and Tushman's (2010) assertion that single measures that capture the degree of exploration versus exploitation are appropriate in most cases (e.g., Lavie & Rosenkopf, 2006; Lin, Yang, & Demirkan, 2007; Uotila et al., 2009), in our study however, competition can induce firms to change their level of commitment to technological innovation (Aghion et al., 2005). More competition can lead to higher (lower) firm commitment to innovation and therefore to both more (less) exploration and more (less) exploitation, without forcing a tradeoff. Alternatively, organizations can decide to explore less (more) without necessarily engaging in more (less) exploitation simply to save resources or to allocate them to other competitive purposes.

An alternative measure of technological exploration and exploitation relies on patent classes (e.g., Manso, Balsmeier, & Fleming, 2019). That is, it classifies technology search strategies as more exploratory if they result in new patent applications in unfamiliar patent classes. In the Online Appendix, we offer a detailed argument for why our measures based on citations capture the underlying constructs more precisely: namely, backward citations are closer to the search process, while patent classes are closer to the outcome of this process, and patent classes overlap to a greater extent with firms' operating product-markets. That said, we also offer robustness tests with this alternative proxy obtaining qualitatively similar results.

[2]Consider a firm that files for a patent application that contains three citations to prior art. Citation A has not been used by the firm in any prior patent applications filed between t–1 and t–5. Citation B was used twice, once in year t–3 and once in year t–4. Citation C was also used twice, in patent applications both filed in year t–2. For our measures, the raw values of technological exploration and technological exploitation for this firm are 1 and 3, respectively.

Our mechanism relating competition to search strategies relies on the different time to fruition between exploration and exploitation. We expect innovations that use familiar knowledge to have a more powerful impact on short-term performance. For example, in 1998, Eli Lilly successfully patented a breakthrough innovation in the field of Alzheimer's disease detection and treatment (US6284221B1), resulting from a 10 years research collaboration with Athena Neurosciences (73% of the citations in the application document were thus familiar to the firm). Ely Lilly's history in the field, and observers' attention to it, were probably among the determinants of the strong short-term stock market reaction (equivalent to a patent valuation of 684 USD millions) and rapid innovation diffusion (with over 80% of the citations coming from applications filed in the first year after the patent granting). On the contrary, Genentech's patent on a method for preparing humanized antibodies (US6407213B1—granted in 2002), which is also in the first percentile of citations received, generated a relatively mild stock market reaction (equivalent to a patent valuation of 60 USD millions) and was slow to stimulate further innovation (only 15% of the citations were received in the first year after the patent granting). Incidentally, 92% of the citations in Genentech's patent were new. This evidence is of course nothing more than anecdotal. In the Online Appendix of the article, we provide quantitative tests to back our theoretical mechanism. In particular, we evaluate the effect of citations on the speed of innovation diffusion, firms' 1 year ahead accounting performance (ROA and cash flow), and short-term stock market reaction on patent granting announcement (using data from Kogan, Papanikolaou, Seru, and Stoffman (2017)). Our evidence supports the contention that technological exploitation increases short-term performance while technological exploration does not.

We aggregate the patent data (applications and citations) at the level of the European Patent Office Worldwide Bibliographic Database (DOCDB) patent family–priority year. These patent families contain patents that cover the same innovations, filed in different patent offices around the world, as well as continuations and divisions.[3] Patents in the same DOCDB patent family refer to the same technical content, so their separate consideration could inflate our patent measures. By aggregating the data at the patent family level, we account for this potential problem. Firms also might increase their use of patent continuations and divisions with the explicit purpose of blocking competitors, which implies a change of their legal but not their technology search strategies. In separate regressions we test the effect of competition on the number of patent continuations and patent divisions filed by a firm, we find no evidence that increased competition is associated with these outcomes.[4]

3.2 | Import penetration and instruments

We start by calculating the level of import penetration for every year and four-digit manufacturing SIC (2000–3999) as a ratio of the value of imports divided by the total value of internal production plus imports. All the data necessary for this calculation come from the NBER website.

As Figure 1 shows, the trend over the sample period is generally upward, such that average import penetration went from 13% in 1990, to 18% in 1998, to 25% in 2006. However, this

[3]Patent continuations add claims to inventions previously disclosed in the parent applications; patent divisions cover different inventions, which have been disclosed in their parent applications.

[4]We find tenuous evidence that import penetration might be positively related with an increase in self-citations. Self-citations are consistent with increasing exploitation and with technological defense strategies aimed at filling the patenting space. These analyses are available on request.

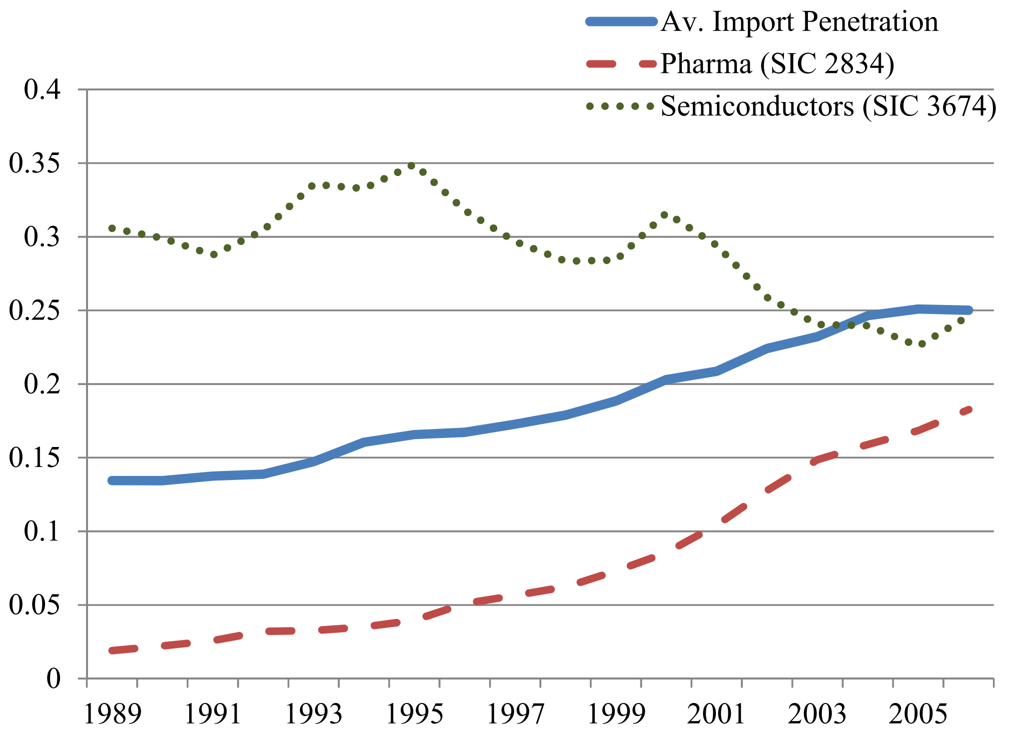

FIGURE 1 Trends in import penetration, average and by sector

tendency is not uniform across industries; some sectors start with a comparatively low level of import penetration and experience an increase in the presence of foreign competitors (e.g., SIC 2834, pharmaceuticals), but for other industries, the trend is opposite (e.g., SIC 3674, semiconductors). For every year in the sample period, our data set contains a variety of combinations of changes in import penetration.

We follow Cuñat and Guadalupe (2009) and refine our measure of import penetration in two steps. First, we find the deviation in import penetration by subtracting the industry mean calculated across all sample years, which ensures that our measure does not capture unobserved differences across industries that correlate with import penetration. Second, we account for whether a firm operates in different manufacturing industries by computing a weighted average (by segment sales) of the level of import penetration experienced by the firm in each of its industries.

The empirical strategy fully exploits the panel nature of our data to include firm- and year-fixed effects that control for unobserved heterogeneity. Notwithstanding this advantage, the results from regressions on import penetration might be subject to endogeneity concerns. For example, reverse causality issues may arise if changes in the level of technological exploration and exploitation exhibited by U.S. firms drive the behavior of foreign executives and their intended presence in the U.S. market (e.g. Becerra et al., 2020). Alternatively, unobservable technology shocks might drive both the choice of technology search strategies by U.S. firms and the decisions of foreign competitors (Bloom et al., 2016). We therefore use current and lagged exchange rates, as well as lagged tariffs, to instrument for import penetration (Cuñat & Guadalupe, 2009; Xu, 2012).

We start by calculating the exchange rate and tariff rate at the sector level. Data on scheduled tariffs come from the World Bank UNCTAD TRAINS data set and are available at the six-digit harmonized system (HS6) product level from 1989. From the TRAINS data set, we download data on scheduled U.S. tariffs for each combination of trade partner and HS6 product category. Then we use the NBER import data to calculate the weight of each trade partner on the imports of every four-digit SIC in 1998, our baseline year. We keep this weight fixed, then use it to compute a weighted average tariff for each combination of SIC4 and HS6 product category. To assign HS6 product categories to SIC4 industries, we use mapping developed by the U.S. Census Bureau and available through the NBER website. Finally, the average scheduled tariff for each industry–year combination is a simple average of the tariffs calculated for all products assigned to that industry.

Our proxy for exchange rate is also calculated at the four-digit SIC level. Following Bertrand (2004), we use the weighted average of the logarithm of the real exchange rate of importing countries, expressed as the amount of foreign currency per dollar. We transform nominal exchange rates into real exchange rates using the trading partners' CPI. Data on CPIs and nominal exchange rates came from the international financial statistics of the IMF. Again, we keep the weight of each trading partner constant throughout the sample period and equal to the share of imports that the country represents for each four-digit SIC in 1998. Similar to the procedure for calculating our import penetration measure, we demeaned and weighted the exchange rates and tariffs to obtain firm-specific measures.

For our instruments to be valid, they must be exogenous and satisfy the exclusion restriction. The dollar is a freely floating currency, and its exchange rate is primarily determined by macroeconomic factors that affect aggregate demand and supply (e.g., interest rates, inflation, and balance of payments between trading partners). None of these factors is likely to be significantly affected by individual firm-level characteristics. Tariff rates instead are the result of international trade agreements and federal policy decisions, which are unlikely to correlate with firm-level innovation strategies. Nevertheless, executives arguably might lobby to increase import tariffs if the firm experiences an increase in competitive pressure. The evidence in Figure 2 should mitigate this concern though. Most of the decline in tariffs concentrates around

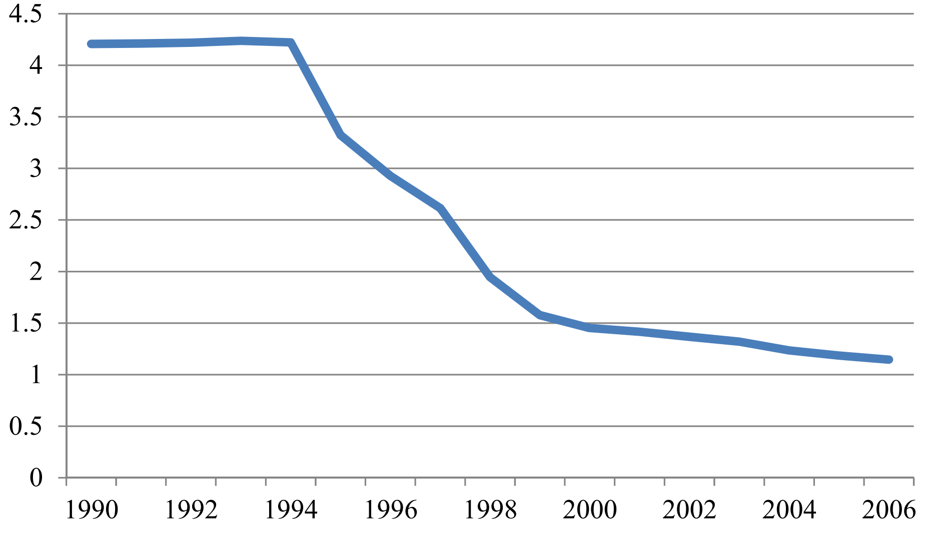

FIGURE 2 Average scheduled tariffs by year

1995, when the Uruguay round of the General Agreement on Tariffs and Trade started being implemented. For example, between 1994 and 1995, the average tariff rate applied for the industries in our sample declined by 21%.

3.3 | Controls and general form of the regression models

All our regressions include year- and firm-fixed effects, plus a set of controls that capture firm- and sector-level differences that affect the propensity to engage in technological exploration and exploitation: firm sales, firm ROA, R&D expenses, firm age, the number of patent applications, the number of citations contained in the patent applications, the patent stock, and the availability of extramural technology. In particular, the inclusion of firm age and the patent stock aims to control for changes in firms' capabilities. Firms' innovation capabilities accumulate over time and arguably depend on the amount of prior success in developing innovations; foundational literature in turn asserts that firms with more consolidated capabilities might overemphasize exploitation at the expenses of exploration (Levinthal & March, 1993; March, 1991). In our research setting, import penetration tends to increase over time (and import tariffs generally decrease), so a risk of confounding the two effects arises, leading us to include appropriate controls. Firm age is approximated using the year of a firm's first appearance in the Compustat database (which started in 1950). In a separate analysis, we split our firm sample according to their exploration/exploitation focus in the prior year. Although the coefficients are less precisely estimated, firms in the two subsamples behave similarly in reaction to import penetration, and both tend to increase their focus on technological exploitation. These results rule out the alternative explanation that firms simply fall back on their accumulated capabilities when competition increases.

Including the supply of extramural technology instead accounts for the possibility that firms might substitute internal innovation with external innovation if they operate in sectors with a well-functioning market for technology (MFT). We use the U.S. Patent and Trademark Office Patent Assignment Dataset (Marco, Graham, & Apple, 2016) to estimate of the total number of patent transactions taking place in a sector in each year of our sample period.[5]

We estimate all our models using the *xtivreg2* command in Stata 16, which implements instrumental variable–generalized method of moments (IV-GMM) models with fixed effects. The general form of the regression is as follows:

$$\ln\left(Y_{f,t}\right) = \alpha_t + \gamma_f + \beta_1 ImportPen_{f,t-1} + \beta X'_{f,t} + \epsilon_{f,t},$$

where $Y_{f,t}$ refers to either technological exploration or technological exploitation; α_t and γ_f are year- and firm-fixed effects, respectively; $ImportPen_{f,t-1}$ is our instrumented measure of import penetration lagged by 1 year; $X'_{f,t}$ is the vector of control variables; and $\epsilon_{f,t}$ is an error term. We cluster *SE*s in all regressions at the firm level to allow for autocorrelation of the error term

[5]Marco et al. (2016) distinguish employee–employer reassignments from transactions among different entities. To obtain an estimate of the MFT for each sector, we built a usage profile for each patent class, by calculating the probability that a patent application in a given patent class belongs to a firm operating in a given SIC sector (Silverman, 1999). In separate analyses, available on request, we also test the effect of import penetration on the sector-level number of patent transactions; these results do not support a positive relationship between the two variables.

within firms and across years. Moreover, to reduce the influence of outliers, we take the natural logarithm of all our dependent variables and controls except for firm age and ROA, which we winsorize at the 1% level.

4 | DESCRIPTIVE STATISTICS AND RESULTS

Table 1 contains the descriptive statistics. For our two dependent variables, we report both the raw value and the transformation used in the regression models. The distribution of these variables is clearly skewed, which justifies our use of logarithmic transformations. Table 2 provides the pairwise correlations, revealing that some variables exhibit considerable correlation, as we would expect. For example, the total number of patent applications naturally is highly correlated with total R&D expenses (.72), technological exploitation (.79), and technological exploration (.92). These high correlations do not create a problem though, because multicollinearity concerns only arise for variables that will be used jointly as controls. The independent variable, import penetration, exhibits a high negative correlation with tariffs (−.58) and a low negative correlation with exchange rates (−.08). The correlation of import penetration with technological

TABLE 1 Descriptive statistics

	Obs.	Mean	*SD*	p25	p50	p75
Dependent variables						
Technological exploration (raw)	8,480	391.51	1,174.69	18.00	58.00	220.50
Technological exploration (ln)	8,480	4.23	1.83	2.94	4.08	5.40
Technological exploitation (raw)	8,480	560.03	2,257.00	2.00	30.00	228.00
Technological exploitation (ln)	8,480	3.45	2.58	1.10	3.43	5.43
Import penetration & instruments						
Import penetration (raw)	8,480	0.2	0.13	0.1	0.17	0.26
Import penetration (mean centered)	8,480	−0.01	0.05	−0.03	−0.01	0.02
Exchange rate (raw)	8,480	2.59	0.72	2.12	2.58	3.15
Exchange rate (mean centered)	8,480	0.02	0.25	−0.12	0.04	0.16
Tariff rate (raw)	8,480	2.57	2.41	0.63	2.22	4.11
Tariff rate (mean centered)	8,480	0.2	1.43	−0.84	−0.01	1.23
Controls						
Sales (ln)	8,480	6.21	2.09	4.57	5.96	7.64
ROA	8,480	0.11	0.14	0.06	0.12	0.18
R&D (ln)	8,480	3.53	1.84	2.15	3.25	4.67
Firm age	8,480	19.09	14.89	7	13	29
Patents applied (ln)	8,480	1.16	1.57	0.00	0.69	1.95
Citations made (ln)	8,480	4.57	1.83	3.37	4.57	5.96
Patent stock (ln)	8,480	4.31	1.97	2.83	4.06	5.49
MFT (ln)	8,480	6.21	1.52	5.22	6.27	7.4

TABLE 2 Correlations

		1	2	3	4	5	6	7	8	9	10	11	12	13
1	Technological exploration	1.00												
2	Technological exploitation	.70	1.00											
3	Import penetration	−.03	.10	1.00										
4	Exchange rate	.05	−.01	−.08	1.00									
5	Tariff rate	.00	−.14	−.58	.06	1.00								
6	Sales	.60	.46	.07	−.01	−.08	1.00							
7	Return on assets	.19	.08	−.07	−.01	.17	.34	1.00						
8	R&D	.64	.57	.13	−.02	−.17	.81	.10	1.00					
9	Firm age	.28	.24	.02	.00	−.01	.50	.19	.31	1.00				
10	Patents applied	.92	.79	−.02	.04	−.01	.63	.15	.72	.30	1.00			
11	Citations made	.94	.88	.03	.03	−.06	.58	.15	.66	.27	.92	1.00		
12	Patent stock	.71	.73	.12	−.01	−.13	.73	.14	.76	0.56	.81	.75	1.00	
13	Market for technology	.18	.22	.16	.04	−.24	.07	−.12	.33	−.12	.25	.21	.20	1.00

exploitation is positive and small (.10), and that with technological exploration is negative and small (−.03).

In Table 3, we report the results from the first-stage regressions. As Model 1 shows, real dollar appreciation decreases import penetration in the same year but increases it with a one-year lag. These results are consistent with the J-curve predicted by monetary economics (Bahmani-Oskooee & Ratha, 2004; Magee, 1973) and with previously published findings (e.g., Cuñat & Guadalupe, 2009). Model 2 replaces exchange rates with tariffs, revealing that higher tariffs are associated with lower import penetration. Finally, Model 3 is a joint test of the instruments. The results show that the effects of both tariffs and exchange rates are robust. Model 3 is the first stage regression of our two-stage analysis below in which import penetration is the instrumented variable.

The validity of our instruments is reinforced by the statistics included in Table 4, together with the results from second-stage regressions. The Kleibergen-Paap LM statistics test the null hypothesis that the model is underidentified (i.e., instruments do not correlate with the endogenous regressors), which is rejected for all models. The modified Kleibergen-Paap *F*-statistics provide a test of whether the model is identified but the instruments correlate only weakly with the endogenous regressors. Weak instruments may produce significant biases in the instrumental variable (IV) estimators. Stock and Yogo (2005) provide a table with critical values of the F-statistics, which in our case correspond to 13.91, 9.08, and 6.46 for the maximum IV relative bias (compared with the bias of the ordinary least square estimators) at 5, 10, and 20%, respectively. The Kleibergen-Paap *F* statistic of most of the models is consistent with IV relative bias of less than 5%, except for Models 7 and 8 in which the maximum IV relative bias is less than 10%. Finally, we report *p*-values from the Hansen–Sargan test of the overidentifying restriction (Hansen J.), which tests the joint null prediction that the IVs are exogenous and uncorrelated with the error term of second-stage regressions. The only exception here is in Model 12, whereas in all other models, the null hypothesis cannot be rejected.

Models 1–2 in Table 4 provide evidence consistent with our theoretical contentions. In Model 1, the effect of import penetration on technological exploration is negative (−1.26; p = .041). In Model 2, the effect of import penetration on technological exploitation instead is

TABLE 3 First-stage regressions

DV: Import penetration	(1)	(2)	(3)
Exchange rate	−0.013		−0.008
	(0.003)		(0.056)
Lag exchange rate	0.019		0.015
	(0.000)		(0.000)
Lag tariff		−0.014	−0.014
		(0.000)	(0.000)
Controls	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	8,480	8,480	8,480
Adj. R^2	.345	.407	.409

Note: The *p*-values are in parentheses, reflecting two-tailed tests for all the variables.

TABLE 4 Main results

	Tech. explore	Tech. exploit	Tech. explore	Tech. exploit	Tech. explore	Tech. exploit	Tech. explore	Tech. exploit	Tech. explore B2B sectors	Tech. exploit	Tech. explore B2C sectors	Tech. exploit
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Lag import penetration	−1.255	3.151							−1.453	3.516	0.426	1.040
	(0.041)	(0.022)							(0.038)	(0.022)	(0.710)	(0.672)
Lag import pen. LTC			−0.968	2.265			−0.184	1.001				
			(0.239)	(0.179)			(0.838)	(0.579)				
Lag import pen. HTC					−2.459	5.002	−2.272	4.279				
					(0.011)	(0.024)	(0.036)	(0.068)				
Sales	−0.040	0.043	−0.048	0.063	−0.028	0.020	−0.030	0.030	−0.025	0.049	−0.061	0.030
	(0.147)	(0.435)	(0.085)	(0.256)	(0.322)	(0.728)	(0.301)	(0.608)	(0.492)	(0.513)	(0.132)	(0.711)
Return on assets	0.099	−0.128	0.102	−0.133	0.103	−0.131	0.104	−0.139	−0.050	0.100	0.297	−0.347
	(0.329)	(0.483)	(0.315)	(0.462)	(0.319)	(0.481)	(0.311)	(0.450)	(0.693)	(0.650)	(0.078)	(0.281)
R&D	0.013	−0.055	0.016	−0.064	0.007	−0.046	0.008	−0.048	0.010	−0.041	0.025	−0.050
	(0.574)	(0.264)	(0.477)	(0.191)	(0.750)	(0.353)	(0.732)	(0.334)	(0.725)	(0.544)	(0.515)	(0.460)
Firm age	−0.080	−0.318	−0.072	−0.337	−0.087	−0.305	−0.086	−0.313	−0.034	−0.272	−0.144	−0.440
	(0.473)	(0.014)	(0.521)	(0.010)	(0.435)	(0.018)	(0.445)	(0.016)	(0.814)	(0.114)	(0.401)	(0.019)
Patent applications	0.396	−0.103	0.395	−0.101	0.399	−0.108	0.398	−0.106	0.414	−0.123	0.374	−0.085
	(0.000)	(0.033)	(0.000)	(0.034)	(0.000)	(0.025)	(0.000)	(0.028)	(0.000)	(0.037)	(0.000)	(0.276)
Total citations made	0.752	0.960	0.752	0.960	0.753	0.958	0.753	0.959	0.745	0.965	0.765	0.944
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Patent Stock	−0.271	0.846	−0.264	0.830	−0.278	0.858	−0.277	0.854	−0.312	0.926	−0.220	0.712
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Market for technology	−0.003	−0.004	0.006	−0.027	−0.018	0.024	−0.015	0.013	−0.001	0.015	−0.012	−0.081
	(0.875)	(0.899)	(0.726)	(0.463)	(0.365)	(0.514)	(0.489)	(0.762)	(0.971)	(0.699)	(0.700)	(0.238)

TABLE 4 (Continued)

									B2B sectors		B2C sectors	
	Tech. explore	**Tech. exploit**	**Tech. explore**	**Tech. exploit**	**Tech. explore**	**Tech. exploit**	**Tech. explore**	**Tech. exploit**	**Tech. explore**	**Tech. exploit**	**Tech. explore**	**Tech. exploit**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,480	8,480	8,480	8,480	8,480	8,480	8,480	8,480	5,260	5,260	3,198	3,198
Kleibergen-Paap LM	145.84	145.84	104.60	104.60	67.80	67.80	86.88	86.88	113.32	113.32	53.34	53.34
Kleibergen-Paap *F*	50.62	50.62	63.45	63.45	15.72	15.72	12.47	12.47	54.37	54.37	28.32	28.32
Hansen J.	0.460	0.133	0.442	0.379	0.910	0.164	0.832	0.275	0.828	0.822	0.103	0.050

Note: The *p*-values are in parentheses, reflecting the two-tailed tests for all the variables.

positive (3.15; $p = .022$). Thus, on average, firms tend to focus on technological exploitation rather than exploration following an increase in import penetration. The magnitude of the effects is substantial; if import penetration were to increase from 15 to 20%, it would generate a 6.3% decrease in technological exploration and a 15.8% increase in technological exploitation.

5 | SUPPLEMENTARY ANALYSIS

Some scholars have argued that the *type* of competition affects the direction of technology search strategies (Polidoro & Theeke, 2012; Rosenkopf & Nerkar, 2001; Toh & Kim, 2013; Toh & Polidoro, 2013). When competition involves products and services that build on similar knowledge, firms tend to defend their market positions by organizing their "inventors for greater search depth with less external collaborative invention, rather than for greater exploratory search via more collaborative invention" (Toh & Polidoro, 2013: p. 1187). When competition involves technology though, emphasizing the exploitation of similar technologies might increase competitive rivalry further and erode profits. Put differently, in technology-based competition, marginal increases in performance and reliability gained through technological exploitation might not be enough, while exploration, by increasing performance variance, might give the firm a better chance to obtain the positive outcomes needed for survival (Levinthal & March, 1993; March, 1991).

To account for different types of competition, we separate imports from LTCs from imports from HTCs. The underlying logic is that rivals from LTCs are more likely to introduce products and services that build on similar knowledge bases and ultimately engage in price-based competition. Instead, rivals from HTCs are more likely to compete on technology. For our analysis, we consider as HTCs, the 15 countries whose entities registered the highest number of patents in the United States during our sample period; all other countries are labeled as LTCs. The validity of this partition is confirmed by the fact that firms from HTCs (e.g. Japan, France, South Korea, UK, and Canada) registered on average 90.7 patents per billion dollar of imports; firms from LTCs (e.g. China, India, Brazil, Russia, and Mexico) instead, registered only 2.6 patents per billion dollar of imports.

For each group of countries, we recalculate our measure of import penetration and the corresponding instruments. As it is possible to see from Models 3–8 in Table 4, the results for import penetration LTC and import penetration HTC are qualitatively similar, even though they vary in their significance levels. In particular, both types of import penetration have negative effects on technological exploration (LTC *coeff.* $= -.97$, $p = .239$; HTC *coeff.* $= -2.46$, $p = .011$), while their effects on technological exploitation are positive (LTC *coeff.* $= 2.27$, $p = .179$; HTC *coeff.* $= 5.00$, $p = .024$). Furthermore, the joint test of the two types of competition in Models 7 and 8 increases the *p*-value of the coefficients but does not affect their sign. Thus, even if the two types of import penetration differ in nature, firms respond to them in a similar fashion, that is, by reducing exploration and increasing exploitation.

The intensity through which import competition affects firms and thus their choices of technology search strategies is likely to be heterogeneous across industries. In Models 9–12 of Table 4, we split the sample according to whether the primary customer in the primary operating market is another firm (B2B industries) or a final consumer (B2C industries), with the logic that foreign competitors represent a different threat to firm survival in B2C versus B2B industries (Zhou & Guillén, 2015). In B2C industries, the threat to firm survival is typically lower, because foreign competitors need to adjust their product offerings to the idiosyncratic features of the host market and overcome liabilities of foreignness. The shift to technological exploitation thus should be more pronounced in B2B industries than in B2C industries. Our results confirm this conjecture: Import penetration is strongly linked to both technological exploration (*coeff.* = −1.45, p = .018) and exploitation (*coeff.* = 3.52, p = .022) in B2B industries, while its association with the technological exploration and exploitation is weaker in B2C industries (exploration *coeff.* = .43, p = .710; exploitation *coeff.* = 1.04, p = .672). For this analysis, the partition of industries according to the primary customer that they serve comes from Lev et al. (2010).

While changes in competitive intensity brought about by changes in import penetration affect all firms in a given industry, firms' individual responses are likely to display a high degree of heterogeneity, a cornerstone of strategy research. We focus here on traits that make a firm more or less able to cope with the longer time horizon associated with exploration. Firms that are more likely to risk bankruptcy as a result of a competitive threat (i.e., lower resilience) would more aggressively run away from technology search strategies (exploration) that might deplete corporate resources and accelerate organizational demise. Instead, firms that are more likely to survive despite increased competitive intensity (i.e., greater resilience) engage relatively more in exploration and relatively less in exploitation.

Table 5 contains the results of our investigation of how the relationship of import competition with technological exploration and exploitation is moderated by factors that affect a firm's resilience to competition. We examine the effect of operating leverage, diversification, and liquidity. Operating leverage is the percentage of selling, general, and administrative expenses over sales; these costs are sticky and difficult to cut when sales decline (Anderson, Banker, & Janakiraman, 2003). Accordingly, operating leverage makes firms more prone to run out of resources and face bankruptcy (Altman, 1971). Model 1 shows that the interaction of operating leverage with import penetration is negative on technological exploration (*coeff.* = −7.56; p = .006). Similarly, product diversification diminishes bankruptcy risks, because firms can subsidize losses suffered in one sector with profits generated in another (Singhal & Zhu, 2013). For diversification proxy we use the entropy measure. In Model 3, the interaction between diversification and import penetration is positive (*coeff.* = 1.51; p = .040). Finally, firms with more liquidity should be more prone to engage in exploration, because their additional financial resources create a cushion and help them absorb initial losses due to exploration. We measure liquidity as the natural logarithm of the amount of cash and short-term investments held by the firm; Model 5 shows that the coefficient of the interaction is positive as expected, though we cannot reject the null hypothesis that it is equal to 0. On the basis of these findings regarding exploration, it seems surprising that operating leverage, diversification, and liquidity do not influence firms' investments in technological exploitation, as indicated by the larger p-values of the interaction terms in Models 2, 4, and 6. Together, these findings suggest that firms might view technological exploitation as a sort of baseline response to import penetration. Because technological exploration is not a useful response to immediate threats though, the extent to which firms abandon it seems to depend directly on their individual risk of failure.

6 | COMPETITION AND TECHNOLOGY SEARCH STRATEGIES: DIFFERENCE-IN-DIFFERENCES DESIGN

In this section we implement a DiD design based on large tariff cuts to test the robustness of our findings with a different identification strategy. By comparing groups of treated and control firms with the same sample period, the chance of misattributing an effect that is actually due to

TABLE 5 Moderators

	Tech. explore (1)	Tech. exploit (2)	Tech. explore (3)	Tech. exploit (4)	Tech. explore (5)	Tech. exploit (6)
Lag import penetration	1.747	0.271	−1.355	2.709	−1.793	3.482
	(0.131)	(0.903)	(0.027)	(0.046)	(0.082)	(0.102)
Op. leverage × lag imp. pen.	−7.561	6.494				
	(0.006)	(0.160)				
Operating leverage	−0.031	0.193				
	(0.796)	(0.336)				
Diversification × lag imp. pen.			1.507	−0.174		
			(0.040)	(0.937)		
Diversification			0.038	−0.071		
			(0.186)	(0.276)		
Liquidity × lag imp. pen.					0.115	−0.103
					(0.431)	(0.732)
Liquidity					−0.001	0.003
					(0.928)	(0.863)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,018	8,018	8,480	8,480	8,480	8,018
Kleibergen-Paap LM	134.244	134.244	144.703	144.703	148.705	148.705
Kleibergen-Paap *F*	19.904	19.904	26.657	26.657	25.950	25.950
Hansen J	0.219	0.040	0.282	0.145	0.693	0.347

Note: The *p*-values are in parentheses, reflecting the two-tailed tests for all the variables.

a change in firms' capabilities is small. In addition, with this analysis we can determine how firms' reactions to competition evolve over time. For example, do firms rebalance their technology search strategies once the environmental conditions in their sector stabilize, or is the switch toward technological exploitation permanent?

We develop the DiD design in accordance with prior studies that address the effect of competition (Flammer, 2015; Frésard, 2010; Frésard & Valta, 2016); in particular, we use large tariff cuts in four-digit SIC sectors as a treatment dummy variable. The average tariff rate is a strong predictor of import penetration, and tariff cuts are unlikely to be reversed in the short run, making them appropriate for this type of analysis. For each four-digit SIC sector, we know the average scheduled tariff rate. To separate important tariff reductions from small fluctuations, we follow Frésard (2010), Frésard and Valta (2016), and Flammer (2015) and include a tariff cut only if it exceeds the average tariff variation calculated for that industry, across the entire sample period, by three times. Then, to confirm that the identified events have some economic significance, we require the tariff rate in the year before the tariff cut to be at least 1%. We thus identify 38 tariff cuts events in different SIC4 industries, most of which took place between 1995 and 1998 (2% after that date).

TABLE 6 Matching descriptive details

	Treated	Control	*p*-Value difference
Firms	137	137	
Firm years	628	758	
Pre-shock mean values			
Technological exploration	3.89	3.72	.413
Technological exploitation	2.44	1.94	.129
Sales (ln)	5.63	5.63	.437
Return on assets	0.12	0.12	.805
R&D (ln)	2.50	2.81	.025
Firm age	12.43	10.67	.222
Patent applications (ln)	1.84	1.91	.883
Citations made (ln)	4.21	3.96	.268
Patent stock (ln)	3.47	3.05	.311
Market for technology (ln)	5.16	5.24	.697

The final sample for the analysis consists of 137 treated firms and 137 control firms. The treatment group includes firms that operate in a primary sector that experienced one (and only one) tariff cut and no tariff raises during the entire sample period. We select the control firms in two steps. First, we form a pool of potential candidates by identifying firms that operate in primary sectors that experienced neither tariff cuts nor tariff raises during the sample period. Second, for each treated firm, we use the *mahapick* command in Stata 16 to select a control firm operating in the same two-digit SIC in the year of the tariff cut, which in the pre-shock years exhibited the closest difference between the number of new and familiar citations in the average patent application.[6] By matching on this latter dimension, we ensure that prior to the shock, treated and control firms follow technology search strategies that are comparable to a certain extent, suggesting that before the shock treatment and control groups had similar technological capabilities.

For the analysis, we compare the behavior of treated and control firms in the 5 years prior to the shock against the behavior of these two groups in the 5 years after it. Table 6 contains the descriptive statistics that show that the two groups contain organizations that, prior to the tariff cut, are comparable. That is, the treated and control firms are very similar in terms of technological exploration (3.89 for treated firms and 3.72 for control firms, $p = .413$) and technological exploitation (2.44 vs. 1.94, $p = .129$). The control firms have a slightly higher R&D intensity (2.50 vs. 2.81, $p = .025$). Yet their patent stock is similar (3.47 vs. 3.05, $p = .311$), as are the average numbers of patent applications (1.84 vs. 1.91, $p = .883$) and citations in patent applications (4.21 vs. 3.96, $p = .268$). We include all these characteristics as controls in our regressions to account for the remaining differences.

[6]The *mahapick* command selects as control observations those with the closest Mahalanobis distance, calculated on the set of matching covariates. In our case, we impose the SIC2 and year as restrictions, so the distance is calculated only on the average difference between new and familiar citations per patent application. We avoid using the other matching covariates, because the pool of potential control candidates for each treated observation is rather small.

FIGURE 3 Difference between new and familiar citations in the average patent application

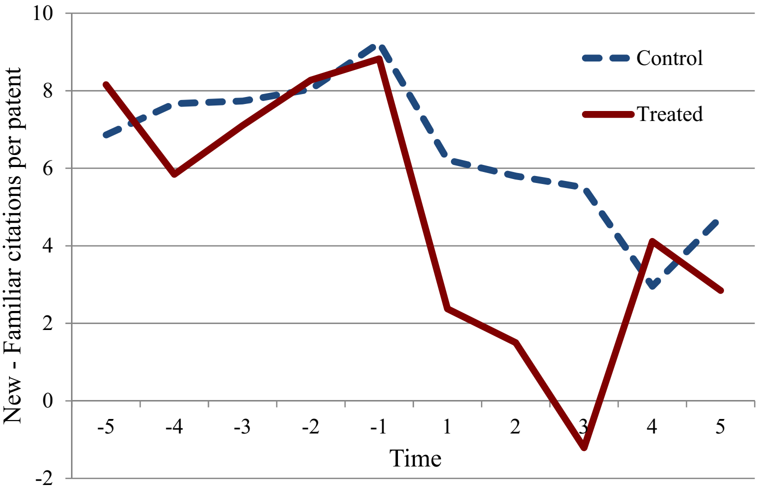

Figure 3 provides initial descriptive evidence pertaining to how competitive shocks affect firms' patenting behavior. For both the treatment and control groups, we plot the evolution of the average patent application in terms of the difference between new and familiar citations. The trend is similar across groups in the years between *t*–1 and *t*–5, but after the shock, treated firms start using considerably more familiar knowledge for their innovations. This behavior continues until year $t + 3$; after that point, treated firms appear to recover their exploration, and the average patent application in $t + 4$ and $t + 5$ looks similar to that of control firms.[7] Figure 3 thus suggests that, after a competitive shock, affected firms first focus on exploitation, then recover their exploration efforts once the immediate threat to their survival has been mitigated. This evidence is purely descriptive though.

To check these results, we test them within a standard regression framework. Table 7 contains eight models to test the effect of tariff cuts on technological exploration and technological exploitation. All models feature clustered *SE*s at the firm level and eight control variables: firm sales, ROA, R&D expenses, firm age, the number of patent applications, the number of citations contained in patent applications, patent stock, and MFT. In addition, Models 2, 4, 6, and 8 include firm-fixed effects. For the baseline test to confirm the results obtained with the instrumented regressions, we define two dummy variables: treated and post. Treated is equal to 1 if the observation belongs to a firm affected by a tariff cut, and 0 otherwise. Post equals 1 if the observation pertains to the period after the shock ($t + 1$ to $t + 5$). With the interaction treated × post, we test for whether the average level of technological exploration (technological exploitation) is lower (higher) among treated firms in the period after the shock. For our analysis over time, we substitute the post dummy with five dummy variables, Post 1 to Post 5, each equal to 1 in one of the 5 years of the post-shock period. The interactions of treated with these five dummies capture whether technological exploration (exploitation) is lower (higher) among

[7]The downward trend in exploration exhibited by the control firms too is likely the result of both increased competition and the accumulation of larger patent stocks. The average tariff rate decreases in control sectors by 8.6% between the pre- and post-shock period, moving from 3.39 to 3.10%. This change is dwarfed in comparison with that in the treated sectors, in which the average tariff rate decreases 53%, from 4.6 to 2.2%. Furthermore, the average patent stock increases for most firms (as logically expected) between the pre- and post-shock periods. The probability of observing exploitation increases with the size the installed knowledge base of the firm, so we include patent stock as a control variable in the regressions.

TABLE 7 Difference-in-differences estimation

	Tech. exploration				Tech. exploitation			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treated*Post	−0.109	−0.141			0.330	0.433		
	(0.087)	(0.022)			(0.042)	(0.009)		
Treated*Post 1			−0.097	−0.160			0.320	0.513
			(0.266)	(0.065)			(0.117)	(0.015)
Treated*Post 2			−0.143	−0.196			0.341	0.480
			(0.124)	(0.045)			(0.118)	(0.030)
Treated*Post 3			−0.231	−0.228			0.252	0.246
			(0.046)	(0.041)			(0.276)	(0.268)
Treated*Post 4			0.010	−0.017			0.232	0.337
			(0.914)	(0.854)			(0.304)	(0.144)
Treated*Post 5			−0.051	−0.021			0.600	0.554
			(0.608)	(0.812)			(0.014)	(0.018)
Treated	0.012		0.012		0.022		0.023	
	(0.733)		(0.726)		(0.835)		(0.830)	
Post	−0.051	−0.040			0.222	−0.145		
	(0.182)	(0.502)			(0.045)	(0.374)		
Post 1			−0.047	−0.032			0.097	−0.226
			(0.380)	(0.659)			(0.500)	(0.258)
Post 2			−0.034	0.003			0.260	−0.196
			(0.590)	(0.970)			(0.096)	(0.384)
Post 3			−0.019	−0.000			0.284	−0.177
			(0.711)	(0.998)			(0.071)	(0.451)
Post 4			−0.129	−0.112			0.417	−0.120
			(0.065)	(0.272)			(0.005)	(0.632)
Post 5			−0.034	−0.049			0.099	−0.396
			(0.646)	(0.680)			(0.566)	(0.184)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Observations	1,386	1,386	1,386	1,386	1,386	1,386	1,386	1,386
Adj. R^2	.926	.799	.926	.799	.774	.588	.774	.587

Note: The *p*-values are in parentheses, reflecting the two-tailed tests for all the variables.

treated firms in that year of the post-shock period, compared with the 5 years preceding the tariff cut. According to the trend suggested by Figure 3, the interactions should be increasingly negative on technological exploration (and positive on technological exploitation) up until year $t + 3$, after which their magnitude and significance should decrease.

Models 1–4 test the effect of tariff cuts on the average level of technological exploration, and Models 5–8 perform the same test for technological exploitation. As expected, the coefficient of the treated × post interaction is negative for technological exploration (−.141; $p = .022$, Model 2) and positive for technological exploitation (.433; $p = .009$, Model 6). Models 3, 4, 7, and 8 instead test for the trend over time. The results largely concur with Figure 3. Notably, the coefficients of the treated × post interactions on technological exploration grow increasingly negative until year $t + 3$, and after that, the average level of technological exploration among treated firms appears indistinguishable from that of the control group. Consistently, the coefficients for technological exploitation are positive in the first 2 years after the shock, then decline in both magnitude and significance in later years (with the exception of year $t + 5$).

Finally, Models 1–8 in Table 8 present a simple test to determine if there are any benefits associated with a strategy that dynamically adjusts the investment in technological exploration or exploitation. We split the sample depending on whether a firm has been delisted by year $t + 6$ after the shock.[8] Models 1 and 4 contain the results of the estimation with the subsample of firms whose stock was still floating 6 years after the shock, whereas Models 5–8 contain the results for delisted firms. Treated firms exhibit an 11% higher probability, relative to control firms, of being delisted in this timeframe, in support of the negative nature of this outcome and its link to the tariff shock. Furthermore, this analysis reveals that our results regarding how firms adjust their levels of technological exploration or exploitation depend specifically on the firms that survive. In Models 1 and 3 for example, the coefficients of the treated × post interactions on technological exploration and technological exploitation are −.147 ($p = .030$) and .522 ($p = .008$), respectively. None of the coefficients of interest appears to have an effect in the analysis with delisted firms. These findings resonate with the results of a recent study by Fitzgerald et al. (2020), which shows that firms focused on technological exploitation obtain better short-term performance, measured as both return on assets and operating cash flow, which arguably improves their chances of survival in the event of a competitive shock.

7 | DISCUSSION AND CONCLUSIONS

We investigate the effect of competition due to import penetration on technology search strategies. Specifically, we argue that when companies face tight profit margins and increased risk of failure as a consequence of import penetration, they might favor technology search strategies (exploitation) that yield results before they run out of business, while turning away from technology search strategies (exploration) that entail benefits in the future.

Our empirical analysis provides causal evidence that firms react to competition due to import penetration by focusing on technological exploitation; the strength of the reaction increases with greater firm vulnerability. Furthermore, we show that the shift toward technological exploitation is temporary, and firms recover their exploration level about 3 years after the competitive shock. This behavior also appears beneficial, in that it characterizes firms that have survived the competitive shock but not those that have succumbed to it.

[8]With a manual check of forms submitted to the Securities and Exchange Commission before their delisting, we can identify the reason for this outcome for most of the delisted subsample. In most of the cases, it involved bankruptcy (10 treated and 5 control firms) or acquisition (54 treated and 45 control firms). Thus, treated firms have a 10.2% higher probability of filing for bankruptcy or being acquired. Both outcomes represent negative events; the probability of observing an acquisition increases when poor performance and financial distress depress a company's stock price.

TABLE 8 Diff in diff, split by continued stock market listing (to $t + 6$)

	Listed in $t + 6$				Delisted in $t + 6$			
	Exploration		Exploitation		Exploration		Exploitation	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treated*Post	−0.147		0.522		−0.136		0.110	
	(0.030)		(0.008)		(0.403)		(0.718)	
Treated*Post 1		−0.124		0.592		−0.228		0.245
		(0.255)		(0.029)		(0.137)		(0.465)
Treated*Post 2		−0.272		0.706		0.026		−0.245
		(0.011)		(0.007)		(0.913)		(0.525)
Treated*Post 3		−0.245		0.356		−0.211		−0.129
		(0.046)		(0.168)		(0.483)		(0.763)
Treated*Post 4		−0.027		0.334		−0.069		1.057
		(0.762)		(0.189)		(0.905)		(0.161)
Treated*Post 5		−0.041		0.606		0.188		1.000
		(0.646)		(0.014)		(0.625)		(0.403)
Post	−0.003		−0.454		−0.072		0.484	
	(0.959)		(0.019)		(0.655)		(0.136)	
Post 1		−0.036		−0.531		−0.001		0.304
		(0.668)		(0.036)		(0.992)		(0.401)
Post 2		0.061		−0.644		−0.174		0.823
		(0.483)		(0.023)		(0.423)		(0.023)
Post 3		0.010		−0.527		−0.110		0.679
		(0.899)		(0.072)		(0.621)		(0.126)
Post 4		−0.112		−0.429		−0.213		−0.007
		(0.259)		(0.179)		(0.693)		(0.991)
Post 5		−0.067		−0.755		0.106		−0.631
		(0.580)		(0.042)		(0.768)		(0.598)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	929	929	929	929	457	457	457	457
Adj. R^2	.831	.831	.623	.622	.718	.716	.486	.489

Note: The *p*-values are in parentheses, reflecting the two-tailed tests for all the variables.

These findings contribute to literature on exploration, exploitation, and the environment (Cao et al., 2009; Jansen et al., 2006; Luger et al., 2018; Posen & Levinthal, 2012; Voss et al., 2008) by showing that when the threat to company survival is imminent, exploration, as an inherently long-term oriented activity, might be paused. We expect this finding to hold in corporate domains where moving along a new learning curve requires substantial time and investment, such as corporate innovation. In different settings or for different activities, the learning curves associated with exploration might be so steep that it is viable, even in the face of greater competition (Voss et al., 2008). For example, import competition might spur exploration in manufacturing strategies associated with offshoring some production to low-wage countries (Mion & Zhu, 2013). Likewise, the effect of import penetration on search strategies might differ for other functional domains, such as marketing, human resource management, or mergers and acquisitions.

Our findings complement the literature that has studied the relationship between product market competition and firm incentives to innovate. This literature has found that competition decreases incentives to innovate when firms are technology laggards, while it fosters innovation for those firms at the technology frontier (Aghion et al., 2001; Aghion et al., 2005). In contrast, our results show that, regardless how technologically advanced is the country where competition is coming from, firms always increase exploitation and decrease exploration. Thus, while the type of competition firms face affects their overall incentives to innovate, it does not seem to change the type of innovation firms pursue.

These results also are relevant to literature on ambidexterity. Scholars highlight an apparent disconnect between ambidexterity literature and the wider domain of exploration/exploitation research (Luger et al., 2018; Raisch, Birkinshaw, Probst, & Tushman, 2009). The former implicitly assumes an optimization logic (Andriopoulos & Lewis, 2009; Gibson & Birkinshaw, 2004; Patel, Messersmith, & Lepak, 2013), predicting that a close match between exploration and exploitation improves both short-term performance and long-term survival. The latter highlights multiple instances in which firms can benefit by focusing on either of the two activities (Jansen et al., 2006; Posen & Levinthal, 2012). Ambidexterity literature also typically addresses organizational arrangements that facilitate ambidexterity (cf. Cao et al., 2009) and ignores the effects of environmental conditions on the optimal mix of technology search strategies. In acknowledging this problem, Luger et al. (2018) argue that ambidexterity might be detrimental to firm performance in environments characterized by discontinuous rather than incremental change. Our findings complement such evidence, by showing that firms are dynamic and responsive to the environment in managing technology search strategies. Contrary to theories of inertia though (Hannan & Freeman, 1984; Levinthal & March, 1993), we find that firms eventually return to exploration, after focusing on exploitation immediately after the shock.

Finally, some limitations of this study suggest potential avenues for further research. First, our findings are limited to the relationships of technological exploration, technological exploitation, and competition. It would be interesting to investigate if firms react to the same shock in other domains of corporate activity, such as marketing, human resource management, or mergers, as well as to determine if firms are equally reactive to other types of shocks, such as technological or regulatory shocks that affect economic uncertainty in the environment. Second, we cannot identify whether competition affects firms' propensity to enter into R&D partnerships with external actors. We control for the extent of technology markets in the empirical analysis to ensure that the availability of external technology does not affect our results, but firms might intensify collaborations with universities, for example, to reduce internal exploration costs. Alternatively, they might terminate such relationships to prevent potential knowledge spillovers to competitors. These pertinent questions are broad enough to constitute a foundation for ongoing research, so we encourage efforts to address them.

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DATA AVAILABILITY STATEMENT

Part of the data that supports the findings of this study was derived from sources available in the public domain and part from sources available under license:

- Import data and patent data from the National Bureau of Economic Research (NBER): https://www.nber.org/
- Exchange rates and consumer price indexes from the International Monetary Fund (IMF): https://data.imf.org/
- Trade tariffs data from the World Bank: https://databank.worldbank.org/
- Company-level accounting data from Standard & Poor's Compustat through WRDS: https://wrds-web.wharton.upenn.edu/

ORCID

Raffaele Morandi Stagni https://orcid.org/0000-0003-4835-4564
Andrea Fosfuri https://orcid.org/0000-0001-6584-240X
Juan Santaló https://orcid.org/0000-0002-0339-3343

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of this article.

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