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Unpacking the Impact of Product-Market Competition on Innovation Strategies: Exploration versus Exploitation

Raffaele Morandi Stagni
IE Business School
Strategy
rmorandi.phd2016@student.ie.edu

Andrea Fosfuri
Bocconi University
Management and Technology
andrea.fosfuri@unibocconi.it

Juan Santalo
IE Business School
Strategy Department
juan.santalo@ie.edu

Abstract
This paper studies how product-market competition affects firms’ innovation strategies. Do firms respond to tougher competition by searching for completely new solutions (exploration) or do they defend their position by improving current solutions (exploitation)? To obtain exogenous variation in product-market competition and estimate its causal effect on innovation strategies, we exploit changes in import penetration, which we instrument using exchange rates and scheduled tariffs. We find that tougher product-market competition causes an increase in technological exploitation and a decrease in technological exploration. Consistently, firms lower their investment in innovation activities and generate patents that are more incremental and therefore receive fewer citations. We expand our analysis by investigating the effect of product-market diversification; a factor that we argue should moderate firms’ survival concerns. Our results show that, as product-market competition increases, diversified firms engage in comparatively less exploitation and comparatively more exploration than their single-segment counterparts.

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Keywords: Competition, Exploration, Exploitation, Diversification, Innovation
INTRODUCTION

Innovation is considered a key strategic response to changing environmental conditions (Teece, Pisano, & Shuen, 1997). One of the most important environmental changes faced by companies in the last fifty years has been the increased competition brought in by globalization, with the ratio of imports to GDP more than doubled between 1970 and 2010. Despite a wealth of studies in economics that have looked at the effect of competition on total innovative output (e.g. Aghion, Bloom, Blundell, Griffith, & Howitt, 2005; Bloom & Draca, 2016), we know relatively little about how firms adjust their innovation strategies by rebalancing the choice between exploration and exploitation activities (March, 1991) when confronted with increasing competitive pressures. This paper provides a rigorous attempt to investigate the impact of product-market competition on firms’ innovation strategies by focusing, in particular, on the allocation of resources between exploitative and explorative activities. We exploit changes in import penetration, to obtain exogenous variation in product-market competition and estimate its causal effect on innovation strategies.

Unpacking the effect of competition on firms’ innovation strategies is relevant for at least two reasons. First, theories of organizational learning attribute a central importance to knowledge search mechanisms in allowing adaptation to changing environments (Levinthal & March, 1981; Winter, 1971). Nevertheless, with few exceptions (e.g. Jansen, van den Bosch, & Volberda, 2006; Voss, Sirdeshmukh, & Voss, 2008), little empirical work exists that carefully studies the implications of competition on firms’ innovation strategies. Second, Arora et al. (2015) show that starting from the 1980s large corporations have consistently decreased their rate of investment in scientific research to focus on the development of commercial knowledge (i.e. patents). In a way, firms’ engagement in basic research can be considered the purest form of exploration. Returns
from developing scientific knowledge are typically very distant as the potential for commercial application of any discovery is unknown. Therefore, a decrease in the production of scientific research already constitutes a shift in the exploration-exploitation balance.

We contend that the trend exposed by Arora et al. (2015) is indicative of a change in the way firms approach innovation that it is not limited to basic research. Figure 1 contains a simple analysis of citations in patent applications over the period 1989-2006. Following Katila and Ahuja (2002), we classify a firm’s use of a citation as exploitative if the firm has already used the same citation in patent applications made in previous years, vice-versa the citation is classified as explorative. The tendency that emerges is clear; firms are increasingly reusing familiar knowledge in the development of innovations.

Insert Figure 1 About Here

To account for reasons behind this change in innovation strategies, in this study we focus on product-market competition and in particular on foreign competitive pressure. While the economies of most developed countries have been undergoing many important changes in the last half-century, the increased exposure to international trade is certainly one of the most significant (Krugman, Cooper, & Srinivasan, 1995). This change in environmental conditions is largely the result of decreasing barriers to trade (Baier & Bergstrand, 2007) and of the development of information and communication technologies (Freund & Weinhold, 2004). As a result of these

1 Following Katila and Ahuja (2002) we use a time span of 5 year (t-1 to t-5) for the classification of citations.
factors, according to World Bank data the world-wide percentage of imports of goods and services to GDP rose from 13% to 28% in the forty years between 1970 and 2010.

We argue that to formulate predictions about the consequences that changes in competitive pressure have on the allocation of resources between the exploration of new knowledge and the exploitation of existing knowledge, one needs to make critical assumptions about the nature of firms’ goals. Indeed, we believe that differences in these assumptions are at the root of the contrasting predictions that can be found in the empirical literature (Jansen et al., 2006; Voss et al., 2008). To address this issue, in the next section, we reconsider the model formulated by March (1991) in his seminal paper. Using March’s model we show that, when the primary objective of the firm is to achieve better results than competitors, that is, a competitive advantage, then, tougher competition leads to an increased extent of exploration. On the contrary, when the firm goal is just survival, exploitation will be the strategy of choice.

Unfortunately, management literature does not offer much guidance in establishing the preeminence of one organizational goal over the other. In fact, theories with their roots in economics, such as the Resource Based View (Barney, 1991; Peteraf, 1993), have traditionally focused on competitive advantage as the ultimate corporate goal. Perspectives coming from sociology instead, such as Institutional Theory (Aldrich & Fiol, 1994), have mostly considered survival as the organizational target for success. In this study, we capture the tension between the two organizational goals in the form of competing hypotheses and we test them in the domain of technology development.

While testing the effect of competition on exploration and exploitation provides us with insights about whether firms, on average, give preeminence to surviving or they strive to achieve a competitive advantage, arguably both organizational goals are important. In particular, factors
that attenuate concerns for survival should encourage exploration. Vice-versa, factors that increase the probability of failure should increase exploitation. To test this idea, we focus on the extent of product-market diversification as diversified companies are less concerned about survival than single-segment firms. We argue that, as competition increases, diversified firms should engage in comparatively higher degrees of exploration and comparatively lower degrees of exploitation than their single-segment counterparts.

We test our hypotheses on a panel sample of U.S. manufacturing firms, which spans the years between 1991 and 2006. Following prior literature we use changes in import penetration to proxy for changes in the intensity of product-market competition experienced by U.S. firms (e.g. Bowen & Wiersema, 2005), and correct for potential endogeneity biases by using tariffs and exchange rates as instrumental variables (Cuñat & Guadalupe, 2009; Xu, 2012). To understand the broader picture of how product-market competition affects innovation strategies and choices, we use six different dependent variables in our estimations: R&D Expenses, Exploration, Exploitation, Self-Citations, Patents Application, and the Number of Citations Received by the patents filed by the focal company.

The results from the empirical analyses return a coherent story about the effect of competition on innovation strategies. Consistent with firms valuing survival more than competitive advantage, our results show that firms react to competitive pressures by decreasing their investment in R&D, decreasing exploration and increasing exploitation. As a consequence, firms tend to produce patents of lower quality as measured by the number of forward citations received. Furthermore, we also find support for the prediction that product-market diversification helps in sustaining exploration when competition increases. In fact, diversified firms respond to increased competitive pressures by engaging in comparatively higher degrees of exploration and
in comparatively lower degrees of exploitation then single-segment firms. Patents of diversified firms in turn receive more citations. However, this comes at the cost of producing fewer patents, as diversified firms do not exhibit higher levels of investment in R&D then single segment firms when competition increases.

Results from this study are interesting for scholars addressing the environmental antecedents of exploration and exploitation (e.g. Jansen et al., 2006; Posen & Levinthal, 2012) and also for scholars with a specific research interest in ambidexterity (Gibson & Birkimshaw, 2004; Tushman & O’Reilly, 1996). With regard to the former, most existing work has focused on investigating the role of uncertainty in terms of environmental dynamism (Jansen, Bosch, Volberda, & Van Den Bosch, 2005; Posen & Levinthal, 2012; Sørensen & Stuart, 2000). Environmental dynamism is a concept different from competitive intensity in that it involves uncertainty about customer preferences, technology and market demand (Dess & Beard, 1984). With some caveats (e.g. Posen & Levinthal, 2012), this literature generally agrees that uncertainty typically leads firms to search for new knowledge as “old certainties” might become no longer valid in a dynamic environment (Hannan & Freeman, 1984; Sidhu, Volberda, & Commandeur, 2004). Instead, we show that predictions about the effect of competition on exploration and exploitation can go both ways depending on the preeminence that organizations give to either survival or competitive advantage. Our empirical results, however, return a one-sided story; tougher competition shifts the exploration-exploitation balance in favor of exploitation, at least for what concerns the functional domain of R&D. Nonetheless, product-market diversification helps in mitigating the effect of competition and in sustaining exploration. With regard to the literature on ambidexterity instead, scholars have highlighted the performance benefits gained by balancing exploration and exploitation (He & Wong, 2004; Katila & Ahuja,
2002). Yet little is known about whether the appropriate balance depends on environmental conditions. Our results provide evidence that it does.

On a final note, our study also informs the debate on the relationship between competition and innovation (Aghion et al., 2005; Bloom & Draca, 2016). While our analysis does not address the effect of competition on the overall amount of innovation generated in an economy, our results call for an increased attention to the type of the innovation that is produced after an increase in competition. This issue is important because innovation is the engine of economic growth, and the fact that firms are increasingly specializing on a narrow knowledge base (Arora et al., 2015) might decrease the rate with which scientific breakthroughs contribute to the improvement of our living standards.

Theory

Background: A look back to the foundational literature

The existing literature looks quite divided when it comes to predict what should be the optimal response to competition in terms of exploration and exploitation. Jansen et al. (2006), for example, argue that financial firms that operate in a competitive environment and that engage in higher degrees of exploitation will obtain better performance, as exploitation will lead to improved customer loyalty and reduced risk. Vice-versa, Voss et al. (2008), in a sample of non-profits professional theatres, show that perceived environmental threat increasingly spurs organizations with sufficient financial resources to engage into higher degrees of exploration in an effort to improve their competitive position. Part of these differences is surely due to the fact that these scholars look at different domains of exploration and exploitation and in very different
contexts. Nevertheless, we believe that the roots of such different views about the benefits of
exploration and exploitation can be better understood through a closer examination of the
foundational literature.

In particular, March (1991) proposes a very simple model to explain how learning activities
affect performance in an ecology of competition. In the model, an organization’s success and
failure depends on its performance relative to that of competitors. In turn, the performance of
each organization in the environment is assumed to be drawn from a normal distribution with
mean ($x$) and variability ($v$). The mean of the distribution reflects organizational ability while the
level of variability reflects organization reliability. The effect of learning activities is represented
in the model through changes in the performance distribution. Exploitation, which constitutes the
refinement of existing knowledge, generally increases both average performance and reliability.
This effect in turn produces an increase in the mean of the performance distribution and a
decrease in the variability. Exploratory activities instead, involve experimentation and the search
for new knowledge. The main effect of these activities is to increase the variability of
performance.

In a set up of this kind, conclusions about whether firms should engage in more
exploitation or more exploration as product-market competition increases, critically depend on
assumptions about the nature of firms’ goals: Do firms attribute more value to finishing first or
do they attribute more value to avoid finishing last? Theory predicts and empirical evidence
shows that after a competitive shock organizations in the lower fringe of the market are pushed
out of business (Trefler, 2004). Given the consequence of having a performance in the low tail of
the industry distribution, the difference between the two types of goals can be better exemplified
by the concepts of competitive advantage and survival. Reliability in performance has a very
different effect on the likelihood of achieving the two types of goals.

In their analysis, Levinthal and March (1993) specifically focus on learning myopia. They
argue that sustained learning (i.e. exploitation) could have a harmful effect on the ability of a firm
to maintain a competitive advantage. In contrast, variability in performance could have a positive
effect on the probability of over performing rival firms, the more so, the larger the total number
of competitors operating in the environment. Indeed, in the extreme scenario in which the number
of competitors is very high, the average performance, becomes irrelevant and the variability,
is the only critical factor that increases the probability of overshooting rivals.

As March (1991) acknowledges, however, the situation is radically different when the
objective of the firm is to avoid finishing last, an outcome that leads to organization demise.
Variability in performance in this scenario increases the probability of performing below the
minim threshold. Exploitation is therefore the preferred strategy because it increases both
reliability and average performance.

So what should we expect firms to do? From the discussion above, we can see how the
choice between exploration and exploitation depends on the preeminence that organizations give
to the goal of surviving vs the goal of achieving a competitive advantage. Unfortunately,
however, the literature in management offers little guidance in formulating predictions. In fact,
the Resource Based View and in general the stream of the management literature with its roots in
the field of economics, has traditionally focused on competitive advantage as the ultimate
corporate goal (e.g. Barney, 1991; Peteraf, 1993). Vice-versa, scholars of Institutional Theory,
Organizational Ecology, and of other perspectives coming from sociology have generally
assumed survival to be the organizational target (e.g. Aldrich & Fiol, 1994; Hannan & Freeman,
Given this uncertainty at the theoretical level we test the following two competing hypotheses:

**H1a:** Increases in product-market competition will push firms to engage in comparatively higher degrees of exploration and in comparatively lower degrees of exploitation.

**H1b:** Increases in product-market competition will push firms to engage in comparatively lower degrees of exploration and in comparatively higher degrees of exploitation.

The two hypotheses test for whether firms on average attribute more importance to surviving rather than achieving competitive advantage. Arguably, however, both organizational goals are important and firms will differ in the degree with which they chose to pursue them based on their characteristics. In particular, organizational factors that make organization demise less likely will spur firms to engage in higher degrees of exploration. The opposite will occur in the presence of organizational factors that increase the likelihood of firm death. In the next section we consider one of these factors: product-market diversification.

*The effect of product-market diversification*

A well-established argument in innovation studies is that investing in a broad knowledge base is less risky in diversified firms because diversification minimizes the chance that resulting innovations will not find applications within the organization (Henderson & Cockburn, 1996; Nelson, 1959). Due to the extended product offering of diversified firms in fact, innovations that are relatively useless in one product-market might provide the firm with unexpected revenue opportunities in a market that, at the inception of the R&D project, seemed completely unrelated.
Examples abound in the corporate world. The famous post-it notes from 3M for instance, are the result of a failure by the same company to develop a super-strong adhesive (Mokyr, 1990). This argument points toward a positive contribution of diversification in reducing the risk associated with single R&D projects. A reduction in the risk of R&D in turn should help sustaining exploration despite the increase in competition.

Furthermore, diversified firms do not face the same risk of failure as single-segment firms (Amihud & Lev, 1981). In the previous section we have argued that, when product-market competition increases, firms may opt for more exploitation and less exploration if the increased competitive pressure puts survival of the firm at stake. However, not all organizations see their mortality chances equally affected as the result of an increase in product-market competition. By definition, diversified firms operate in multiple industries and therefore a surge in competition in one of these industries may not compromise their overall organization survival as much as when firms are focused exclusively on the now highly competitive sector. This means that the negative impact of product-market competition on the incentives to engage in exploration activities is attenuated in diversified firms. Therefore we hypothesize the following:

\[ H2: \text{Increases in product-market competition will be associated with more exploration (and less exploitation) in diversified firms vis-à-vis single-business firms.} \]

**Empirics**

The purpose of this paper is to test the effect of changes in the intensity of product-market competition on firms’ innovation strategy. To accomplish this aim we assemble a panel dataset of U.S. companies by combining data from different sources. We use the Standard & Poor’s
Compustat database to obtain information about firms’ financials, firms’ operating segments, and firms’ expenditures in R&D activities. We use the NBER Patent Database (Hall, Jaffe, & Trajtenberg, 2001) to obtain information about firms’ patent applications and about the citations made and received by the firms’ patents. We use data coming from different NBER datasets (Becker, Gray, & Marvakov, 2013; Feenstra, 1996; RC Feenstra, Romalis, & Schott, 2002; Schott, 2010) to calculate our measure of competition: import penetration. Finally, we also use data on tariffs coming from the UNCTAD TRAINS dataset of the World Bank, and data on exchange rates and Consumer Price Indexes (CPIs) coming from the International Financial Statistics of the IMF for the calculation of our instrumental variables.

The resulting dataset effectively covers the period between 1991 and 2006\(^3\) and it is limited to firms having their primary operations in manufacturing SICs (SIC 2000-3999) as trade information is available only for these sectors. We eliminate from this data firms below 10 million dollars in sales. We use two samples for the analyses. The first sample contains all the firm-years for which there is information available in Compustat. This sample has a total of 16,894 observations belonging to 2,193 different firms. The second sample instead is a subsample of the first and it contains the firm-years in which firms filed patents application. The second sample contains a total of 8,429 observations belonging to 1,317 different firms. The two samples will be used for testing the effect of competition on separate aspects of the firms’ innovation strategy. When discussing our dependent variables in the next session we will delve more deeply into the issue.

The general form of our regression models is the following:

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\(^{3}\) Our dataset is limited by the availability of tariff and patent data. The TRAINS database starts in 1989 and we require two years of lagged observations for our analyses. The patent database ends in 2006.
\[
\ln(Y_{f,t}) = \alpha_t + \gamma_f + \beta_1 ImportPen_{f,t-1} + \beta_2 Diversification_{f,t} \\
+ \beta_3 Div_{f,t} \times ImportPen_{f,t-1} + \beta X'_{f,t} + \epsilon_{f,t}
\]

Where \( Y_{f,t} \) is one of our six dependent variables: R&D Expenses, Patent Applications, Forward Citations, Exploiting Citations, Exploring Citations, and Self-Citations; \( \alpha_t \) and \( \gamma_f \) are respectively year and firm fixed-effects; \( ImportPen_{f,t-1} \) is our measure of import penetration lagged by one year; Diversification is a dummy variable that takes the value of 1 if a firm operates in more than one SIC4 segment; \( X'_{f,t} \) is a vector of control variables which depending on the regression includes the logarithm of sales, firm’s ROA, R&D Expenses, Patent Applications, and the total number of citations made by the patents for which the firm applied; \( \epsilon_{f,t} \) is the error term. We cluster standard errors in all regressions at the firm level to allow for autocorrelation of the error term 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 ROA which we winsorize at the 1% level.

**Dependent variables:**


Our proxy for a firm’s investment in R&D is the natural logarithm of the total R&D expense coming from the Compustat Annual data file. The rest of our measures are calculated using data obtained from the NBER Patent-Assigned data file and the NBER citations data file.
Patent Applications is the total number of patents for which a firm applied in a given year. We account for whether a patent application is filed by multiple companies by dividing the weight of the patent equally between the owners.

Forward Citations is the total number of citations received in the future by the patents filed by a firm in a given year. We correct for citation truncation due to the fact that the patent database ends in 2006 by multiplying the citations received by each patent for a correction factor estimated by Hall et al. (2001). The correction factor takes into account the technological field and the year of patent granting to estimate a grossing up factor that accounts for the citations received by a patent after 2006.

For the calculation of our measures of technological Exploration and Exploitation we base ourselves on the seminal work of Katila and Ahuja (2002). Exploitation captures the extent to which the firm in its patent applications reuses a knowledge base with which is already familiar. In particular, we define the variable as the total number of times that citations in the focal year were repeatedly used in patent applications filed between t-1 and t-5. Exploration instead, captures the extent to which the firm searches for new knowledge to develop innovations. Consistently, the measure is defined as the total number of new citations contained in the patent applications. Again, a citation is defined as new if it was never used in patent applications filed by the firm between t-1 and t-5.

Finally, the last of our dependent variables is self-citations. Self-citations capture the extent to which the firm is building on its prior innovations. To a certain degree it can also be considered another, stricter, measure of exploitation (Sorensen & Stuart, 2000) that might serve

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4 To avoid overinflating the measure we only count repeated usage of the same citation across the different years. As a result each citation can take a value between zero and five.
to further validate the findings. The variable is calculated as the total number of times that the firm cites patents that it owns.

We transform all our dependent variables by taking the natural logarithm in order to reduce the influence of outliers on the estimates obtained from our regression models.

Note that we use separate measures to capture Exploration and Exploitation. While in general we agree with Lavie et al. (2010) in that single measures capturing the degree of exploration vs. exploitation are more appropriate in most cases (e.g. Lavie & Rosenkopf, 2006; Lin, Yang, & Demirkan, 2007; Uotila, Maula, Keil, & Zahra, 2009), the use of separate measures in our study is justified by the fact that competition can induce firms to change their level of investment in R&D. An increase in R&D expenses would be consistent with increased levels of exploration but it wouldn’t necessarily imply decreased levels of exploitation. Firms’ could even increase their level of engagement in the two activities proportionally in order to maintain balance. A similar argument applies in the case in which firms’ decrease their investment in R&D.

We argue that the joint use of the six dependent variables that we consider allows us to gain a deeper insight into firms’ innovation strategies. In fact the variables that we use cover different aspects of firms’ innovative effort. R&D expenses capture the firm’s investment in innovation. The number of patents applications and the citations received by these patents capture different aspects of the innovation outcome from the investment in R&D. Finally exploration, exploitation and self-citation, capture the sources of knowledge used by the firm to develop commercially valuable innovations.
Import penetration and instruments

Our identification strategy for product-market competition is based on the prior work of Cuñat and Guadalupe (2009) and Xu (2012). Consistently, our proxy for competition is import penetration. We start by calculating the level of import penetration, for every year and for every four-digits manufacturing SIC (SICs 2000-3999), as the ratio between the value of imports divided by the total value of internal production plus imports. All the data necessary for this calculation comes from the NBER website. Data on imports were compiled by Feenstra (1996), Feenstra, Romalis and Schott (2002), and Schott (2010)\(^5\), data on the value of shipments at the four-digits SIC level comes from the NBER-CES Manufacturing Industry Database (Becker et al., 2013).

Import penetration arguably is a good depiction of the extent to which foreign competitors are present in the U.S. domestic markets. Figure 2 shows that the trend over the sample period is generally upward. The average level of import penetration went from 13% in 1990, to 18% in 1998, to 25% in 2006. However, this tendency was not uniform across industries. As Figure 2 shows, some sectors start with a comparatively higher level of import penetration and experience a decline in the presence of foreign competitors while for other industries the trend is opposite. As a result, for every year in the sample period our dataset contains a rich combination of changes in import penetration.

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\(^5\) The SICs reported in the import data files are the so-called import-based SICs (MSIC) and they are slightly different from the true U.S. domestic SICs. The difference is due to the fact that U.S. domestic SICs at times depend on the method of processing that was used in the production of a good. This information is not available for imports. For example the SIC 2011 “Meat Packing Plants” and the SIC 2013 “Sausages and Other Prepared Meat” produce many of the same products. The distinction comes about because establishments in SIC 2011 are involved in slaughtering while establishments in SIC 2013 use purchased carcasses. Since it is not possible to determine the source of material for imported meat products, all imports of the sort are assigned to SIC 2011 leaving SIC 2013 with no trade at all. In this paper we correct for this bias by assigning neglected industries an amount of imports based on the ratio between their total value of shipments and the value of shipments of the industries that were used as the destination industries for the products of excluded industries.
For the purpose of our analysis we refine our measure of import penetration by taking two further steps. First, we take the deviation in import penetration by subtracting the industry mean calculated between all sample years. This ensures that our measure does not capture unobserved differences across industries that are correlated with import penetration. Finally, we take into account whether the firm operates in different manufacturing industries by computing an average by segment sales of the level of import penetration experienced by the firm in each of its industries. Taking into account whether the firm operates in multiple industries, instead of considering just the firm’s main operating sector, ensures that our measure is a better reflection of the actual level of import penetration faced by the firm. However it also presents us with further challenges, as our measure becomes dependent on endogenous production decision. To address this concern we keep the weights of the segments fixed and equal to the proportions of sales that the segments represent in 1998. For many firms the product offering changed radically in the years between 1990 and 2006, 1998 is halfway through the sample period and therefore it minimizes this problem.

Our empirical strategy fully exploits the panel nature of our datasets to include firm and year fixed-effects that control for unobserved heterogeneity. Notwithstanding, this advantage, results obtained from regressions on import penetration can still be subject to a number of criticisms in terms of endogeneity. For example, reverse causality issues may arise if changes in

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6 If the focus firm is not present in the database in 1998 to calculate segments weights we use the sales data of the year closest to 1998.
7 We have also repeated our analyses using floating segment weights and the results do not change.
the innovation strategy of U.S. firms drive the behavior of foreign executives and therefore influence their presence in the U.S. market (e.g. Cornaggia, Mao, Tian, & Wolfe, 2015). Further, if firms anticipate changes in the level of imports the estimated effect will depend on the strategy adjustment that takes places after the intensity of competition is manifest. Finally, our proxy for import penetration might be measured with error therefore causing attenuation bias. The presence of any of these problems would entail that the estimates obtained from our regression models are biased. To deal with these endogeneity concerns, we use current and lagged exchange rates as well as lagged tariffs to instrument for both import penetration and for the interaction between import penetration and our diversification dummy8 (Cuñat & Guadalupe, 2009; Xu, 2012).

We start by calculating measures of exchange rate and tariff at sector level. Data on scheduled tariffs comes from the World Bank UNCTAD TRAINS dataset and is available at the six-digits HS (Harmonized System) product level starting from 19899. Scheduled tariffs are superior in comparison to calculated average tariffs because they prevent the instrument from being mechanically correlated with imports10. From the TRAINS dataset we download data on the tariffs scheduled by the U.S. 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-digits SIC in 1998, our baseline year. We keep this weight fixed, and we 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 a mapping developed by the US Census Bureau and available through the NBER website. Finally, we calculated the average scheduled

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8 We use as instruments for the diversification - import penetration interaction the interactions of the diversification dummy with tariffs and exchange rates.
9 Data for 1994 is missing, we impute it from 1993.
10 Average tariffs paid are available through the NBER website. The problem with using average tariffs lies in the fact that these are calculated as the ratio between duties collected and value of imports and the value of imports also enters in the calculation of the import penetration variable. As a result any error in measuring imports would generate variation that mechanically improves the fit on the instrumented variable. Our goal is instead to isolate the variation due to changes in tariffs.
tariff for each industry-year as the simple average of the tariffs calculated for all the products assigned to that industry.

Our proxy for exchange rate is also calculated at the four-digits SIC sector level. Following Bertrand (2004), we define the measure as the weighted average of the log real exchange rate of importing countries expressed in amount of foreign currency per dollar. We transform nominal exchange rates into real exchange rates using the trading partners Consumer Price Index (CPI). Data on CPIs and nominal exchange rates are obtained 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-digits SIC in 1998. Following the procedure used for the calculation of our import penetration measure, exchange rates and tariffs are also demeaned and weighted to obtain firm-specific measure.

For our instruments to be valid they have to be exogenous and satisfy the exclusion restriction. Being the dollar a freely floating currency its exchange rate with other currencies is primarily determined by macroeconomic factors that affect its aggregate demand and supply. Examples are interest rate, inflation and the balance of payments between the U.S. and its 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 and therefore are likely uncorrelated with firm-level innovation strategies. Nevertheless one can still argue that executives might lobby to obtain increases in import tariff
after experiencing an increase in competitive pressure. Figure 3 should mitigate this concern. The graph shows that the trend in tariff rate in the years of the sample period is consistently downwards. In particular, most of the decline in tariffs concentrates in the years around 1995 when the results of the Uruguay round of the General Agreement on Tariffs and Trade (GATT) start being implemented. As an example between 1994 and 1995 the average tariff rate applied in the operating industries of the firms in our sample declined by 21%.

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DESCRIPTIVE AND RESULTS

Table 1 contains the descriptive statistics. For each variable relevant for the analyses we report both the raw value and the value of the transformation used in the regression models. As it is possible to see the distribution of many of the dependent variables is quite skewed, this justifies the use of the logarithmic transformation. For example, the mean value for R&D expenses in the full sample is 147 millions USD while the median is 11 millions USD. For what concerns our independent variables instead, the average value of the diversification dummy is 0.26; this means that 26% of the firm-year observations in the full sample belong to diversified firms. We mean-center import penetration and its instruments to prevent the variables from capturing cross-sector differences that are correlated with import penetration and that would prevent causal inference from our regression analyses. Furthermore, as described in the method section, we use static weights to account for diversification. This helps in addressing the exclusion restriction since it increases the explanatory power of exchange rates and tariffs for
imports and decreases the explanatory power for endogenous production decisions. The mean value of the raw import penetration measure is 0.2 over the sample period with a standard deviation of 0.4. For what concerns the average import tariff rate instead the mean value is 2.56 and the standard deviation is 2.46.

Table 2 reports the pairwise correlations. Many of the variables exhibit very high level of correlation but this is to be expected. For example the total number of patent applications naturally is highly correlated with the total number of citations received (0.80), exploiting citations (0.79), and exploring citations (0.91). A high level of correlation in our case does not constitute a problem because potential multicollinearity issues only affect variables that will be used jointly as controls. For what concerns our independent variable, import penetration exhibits a highly negative correlation with tariffs (-0.61) and a low negative correlation with exchange rates (-0.07). The correlation of import penetration with exploitation is positive and small (0.10), while the correlation of import penetration with exploration is negative and small (-0.03).

Table 3 reports the results from first stage regressions for both the full sample and for the subsample of firm-years with a positive number of patent applications. The results are almost identical. In particular, columns 1 and 4 show that a real dollar appreciation significantly decreases import penetration in the same year while it significantly increases import penetration with a one-year lag. These results are consistent with the J-curve hypothesized in the literature of monetary economics (Bahmani-Oskooee* & Ratha, 2004; Magee, 1973) and they are in line with the findings of recent studies (e.g. Cuñat & Guadalupe, 2009). Columns 2 and 5 instead replace exchange rates with tariffs and show that higher tariffs are associated with lower import penetration. Finally, columns 3 and 6 test the instruments jointly. The results show that the effect of both tariffs and exchange rates remains significant.
Conclusions about the validity of our instruments are further reinforced by the statistics reported in Table 4 together with the results from second stage regressions. We report statistics that test for underidentification, weak identification, and for the over-identification restriction. The Kleibergen-Paap LM statistics test the null that the model is underidentified (i.e. the instruments are not correlated with the endogenous regressors). The null is rejected for all the models. The modified Kleibergen-Paap F statistics test for whether the model is identified but the instruments are only weakly correlated with the endogenous regressors. Weak instruments generate problems to the extent that they produce inconsistent instrumental variable estimators. Inconsistent estimators can be biased if the asymptotic distribution of the estimated parameters deviates substantially from the normal distribution (Stock & Yogo, 2002). Stock and Yogo (2005) provide a table with the critical value of the F statistics for the weak instrument test at the 5 percent confidence level. In our case the critical value is 13.5, while the Kleibergen-Paap F statistic of our models ranges between 84.6 and 25.8. Finally, we report the p-value from the Hansen-Sargan test of the over-identifying restriction (Hansen J). This is a test of the joint null that the excluded instruments are not correlated with the error term from the second stage regressions. The p-value associated with the Hansen J is never significant in any of the models. In particular, it ranges between from minimum of 0.27 in Model 11 to a maximum of 0.91 in Model 12. Therefore the null cannot be rejected.

In our theoretical discussion we have used March’s (1991) model to show that, if the primary objective of firms is to obtain a competitive advantage, than they will engage in more exploration and less exploitation the more competition increases. The opposite will occur if decision makers in organizations attribute more value to surviving rather than obtaining a

---

11 All the statistics reported are robust to violations of the i.i.d. assumption.
competitive advantage. Furthermore, given that the choice of the knowledge strategy also has implication in terms of inputs required and output produced, we also test the effect of competition on other aspect of firms’ innovation.

Models 1 to 6 in table 4 contain the results of the tests of H1a and H1b. In particular, our dependent variables are six: R&D expenses, patent applications, citation received, exploitation, exploration, and self-citations. All regressions include firm and year fixed-effects and control for firm size and profitability. Depending on the specification when necessary we also control for R&D expenses, number of patent applications and the number of citations made in the patent applications. Standard errors are clustered by firm in all specification to allow for autocorrelation of the error term within firm across years.

Model 1 tests the effect of import penetration on firms’ expenditure in R&D activities. The effect is negative and significant (-1.11; p-value<0.05). Model 2 tests the effect of import penetration on the number of patent applications made by the firms. We find no effect. Model 3 tests the effect of import penetration on the number of citations received in by the patents for which the firm applied. Here the effect is negative and highly significant (-7.23; p-value<0.01). Model 4 tests the effect of import penetration on the number of exploiting citations. The effect is positive and highly significant (4.38; p-value<0.01). Model 5 tests the effect of import penetration on the number of exploring citations. The effect is negative and highly significant (-2.20; p-value<0.01). Finally, Model 6 tests the effect of import penetration on the number of self-citations. The effect is positive and marginally significant (1.64; p-value<0.10).

As it is possible to see, these results return quite a unilateral picture supporting the idea that when firms are confronted with increased competition they attribute priority to the goal of surviving. Competition increases exploitation as measured both by both self-citations and as
citations to patent already cited. Exploration instead decreases. As a consequence, considering the exploitation is less costly, firms are able to save in terms of R&D expenses. However, while these savings seem to not affect the production of innovations in terms of number of patent applications, the patents produced are less influential. In fact, competition decreases the total number of citations received in the future by the patents for which the firm applies.

The magnitude of these effects is also highly significant. To put things into perspective these coefficients mean that if import penetration increases by 5 percentage points going for example from 0.15 to 0.20 this produces a 5.6% reduction of firms' investment in R&D, a 22% increase in the number of exploiting citations, an 11% decrease in the number of exploring citations, a 8.2% increase in self-citation, and as a consequence the citations receive by the patents for which the firms apply decrease by 36.1%.

Hypothesis 2 states that diversified firms will choose to engage in comparatively more exploration and comparatively less exploitation after an increase in competition. Model 7 to model 12 in table 4 report the results from the tests. As it is possible to see the hypothesis is confirmed. Model 10 shows that the effect of the interaction between the diversification dummy and competition is negative on exploitation (-3.42; p-value<0.05). Model 11 instead, shows that the effect on exploration is positive (2.24; p-value<0.01). Also, the effect of the interaction on self-citations reported in model 12 is negative (-3.10; p-value<0.01).

The channel through which diversified firms choose to sustain the investment in exploration is however different from that emerged from analysis of the main effects. In fact, model 7 shows that diversified firm do not invest comparatively more resources in R&D than their single segment counterparts. Instead, as reported in model 8, they produce fewer patents (-
2.81; p-value<0.01). Consistently, model 9 shows that the patents that they produce end up being cited more (4.34; p-value<0.01).

Getting back to the example made before these results mean that, as a consequence of the same 0.05 increase in import penetration, diversified firms use 17.1% less exploitative citations, 15.3% less self-citations, and 11.2% more exploratory citations that their single-segment counterparts. Furthermore, they produce 14.1% less patents, but the patents that they produce get cited in the future 11.2% more.

**DISCUSSION AND CONCLUSIONS**

This study addresses the effect of product-market competition on exploration and exploitation in the domain of technological innovation. To accomplish this aim, we reconsider the seminal work of March (1991) to show how different assumptions about the nature of firm goals can lead to opposite predictions about the effect of competition on the balance between the two learning strategies. In particular, when the goal is assumed to be to achieve or maintain a competitive advantage, then firms should react to competition by engaging in comparatively higher degrees of exploration. Vice-versa, when the goal is assumed to be survival, competition should increasingly spur firms to focus on their existing knowledge base.

These differences are due to the opposite effects that performance variability has on the probability of achieving each goal, and to the opposite effect that exploration and exploitation have on performance variability. In particular, by increasing reliability, exploitation reduces the variability of performance while increasing its average level. On the contrary, exploration involves experimentation and the outcomes of experimentation are by definition more uncertain. Performance variability in turn, increases the chance that a firm will obtain either a performance
that it is extremely positive or a performance that is extremely negative in comparison to that of its group of peers. If the firm obtains an extremely positive performance it means that the exploratory effort was successful and the firm now owns a technology that is superior to that of competitors. Therefore in this case the firm achieved a position of competitive advantage. If instead, the firm obtains a performance that is extremely negative it means that the experimentation was a failure. Wasting resources in unsuccessful projects can have nefarious consequences for a firm survival prospects when the environment is competitive (Miller & Friesen, 1983; Trefler, 2004).

Our results show how product-market competition generates strong pressures for efficiency on firms’ investment in technological production. Competition increases the level of firms’ engagement in exploitation and decreases the level of firms’ engagement in exploration. Consistently, firms decrease their investment in R&D and generate patents that are more incremental. These results suggest that when firms face a sharp increase of competition in their environment, firms on average attribute more value to the goal of surviving rather than to the goal of achieving a competitive advantage.

Notwithstanding these findings, we argue that both organizational goals are important and that firms likely try to achieve a balance between them. A natural consequence is that organizational factors that decrease the risk of failure should increase the extent to which firms engage in exploration. In our analysis we consider the role of diversification. Diversification provides the firms with two classes of advantages. It decreases the risk that the results of single R&D projects will not find an application within the organization (Henderson & Cockburn, 1996; Nelson, 1959), and it increases the probability that the negative outcomes of unsuccessful R&D projects will be compensated by the positive outcomes of projects undertaken in other units.
Moreover, diversification reduces the likelihood of firm mortality as a result of increases in product-market competition. Therefore diversification should positively impact the ability of a firm to sustain exploration in the face of competition. Results from the analysis largely confirm this prediction. The more competition increases the more diversified firms exhibit higher degrees of exploration and lower degrees of exploitation than their single-segment counterparts. As a result, diversified firms generate patents with higher impact, even though their total number of patent applications is lower than that of single segment firms.

We argue that these results contribute to both the literature studying the environmental antecedents of exploration and exploitation (Posen & Levinthal, 2012; Voss et al., 2008), and also to the literature on ambidexterity (Gibson & Birkinshaw, 2004; Tushman & O’Reilly, 1996). With regards to the first, we contribute solving apparent contradictions in the literature (Jansen et al., 2006; Lavie et al., 2010), by showing how predictions about the effect of competition on exploration and exploitation depend on assumption about firm goals. Furthermore, our results provide evidence that, as competition increases, firms attribute more value to surviving rather than achieving a competitive advantage. In turn diversification, by reducing concerns for survival, mitigates the tendency of engaging in more exploitation and less exploration. With regards to the literature on ambidexterity instead, scholars have mainly highlighted the benefit obtained by balancing exploration and exploitation (He & Wong, 2004; Katila & Ahuja, 2002). Yet again, this literature has mostly assumed that the organizations’ goal was to obtain superior performance. Little is known about whether the appropriate balance changes when concerns for survival come into play. Our results show that it does.

On a more societal level, these findings are also interesting when combined with those obtained by other recent studies (Arora et al., 2015). They show that as a consequence of
competition firms are increasingly developing in innovations that are more incremental. Therefore, while competition is generally assumed to increase the level welfare in a society, it might also entail some drawbacks in the form of changes in firms’ innovation strategies that up to this point have been underestimated.

On the methodological side we argue that the results obtained from our analyses are particularly robust. We test our hypotheses on a large panel dataset of U.S. manufacturing firms (SICs 2000-3999). The panel nature of the dataset allows for the inclusion of both firm and year fixed effects that control for unobserved heterogeneity at the firm level and unobserved trends. We instrument our independent variable, import penetration, using both exchange rate and tariffs to reduce endogeneity concerns and permit a causal interpretation of the results. Furthermore, apart from testing the effect of competition on exploration and exploitation, we estimate regressions also on other proxies for innovation. This allows us to control for whether the story about the effect of competition on exploration and exploitation is consistent.

Nevertheless, our study also suffers from some limitation. First of all we test for the effect of competition on exploration and exploitation only in the domain of R&D. In recent years the literature has applied the concepts of exploration and exploitation to other functional domains such as marketing (e.g. Lavie, Kang, & Rosenkopf, 2011), and also to structural domains such as the formation of alliances (e.g. Lavie & Rosenkopf, 2006). There is no guarantee that the findings of this study will be generalizable to domains other than the one of technology. In explicitly acknowledging this limitation we join the call of other scholars (Lavie et al., 2010) and try to avoid the problems related to the overgeneralization of the findings that are plaguing the literature on exploration and exploitation. Second, for the purpose achieving a causal interpretation of our findings, our identification strategy uses a proxy of competition that is
actually a proxy of foreign competition. While we believe that our results should be generalizable to increases in the competitive pressure due to the actions domestic players, we are unable to perform an adequate test of the subject matter.


Figure 1: Percentage of exploring and exploiting citations in patents

![Graph showing percentage of exploring and exploiting citations in patents from 1989 to 2005.](image-url)
Figure 2: Trend in import penetration – average and by sector

Av. Import Penetration
Pharma (SIC 2834)
Semiconductors (SIC 3674)
Figure 3: Average Scheduled Tariff by Year
Table 1: Descriptive statistics

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### Table 3: First stage regressions

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Standard errors in parentheses;  + p<0.10  * p<0.05  ** p<0.01
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Standard errors in parentheses;  + p<0.10  * p<0.05  ** p<0.01