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Market Entry by High Technology Startups: The Effect of Competition Level and Startup Innovativeness

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Abstract. We study the level of market competition as a determinant for the propensity of cooperation between startups entering new markets and incumbents operating in these markets. We provide ample empirical evidence suggesting that startups and incumbents are more likely to cooperate in the commercialization of startups' technological innovations in markets with either high or low competition levels than in markets with moderate competition levels. Importantly, we further show that startups' innovativeness has a contingent effect—it encourages cooperation at low-to-moderate levels of competition, but encourages competition at moderate-to-high levels of competition.

Keywords: high technology startups • cooperation • competition • competition level • innovativeness

Introduction

Startups often introduce novel technological innovations that are superior to those offered by market incumbents. Yet, in their early years of market entry, startups are typically inferior to incumbents in terms of their complementary assets, brand recognition, and reputation, which are central to a successful penetration and commercialization of startups' novel innovations (Rothaermel 2001, Singh and Mitchell 2005, Teece 1986). Given this disparity in startups' and incumbents' strengths, both startups and market incumbents debate whether to cooperate on commercializing the startups' technological innovations, or to compete with each other.

Clearly, the two entry modes bear different sets of costs and benefits. For example, while cooperation allows startups to utilize incumbents' superior complementary assets, such cooperation requires them to share revenues with incumbents, who may also take advantage of cooperation to imitate the startups' technological innovations. Interestingly, these costs and benefits vary not only across firms but also across *markets*. Indeed, some markets are typically characterized by cooperation between incumbents and startups in the commercialization of startups' innovations through licensing agreements and strategic alliances. In contrast, there are markets where startups typically enter by competing head-on with market incumbents. As Gans et al. (2002, p. 571) note: "In the biotechnology industry, cooperation between start-up innovators and more established firms is the norm. . . . On the other hand, start-up innovators in the electronics industry often [earn] their innovation rents through product market entry and competition with more established firms."

In this study, we examine the effect of competition level on startups' entry mode. In markets with high levels of competition, market shares and profit margins are typically small and hard to sustain for both startups and incumbents (Porter 1980, Schmalensee 1989). Specifically, markets with high competition levels are typically characterized by a large number of rival firms and a low degree of differentiation (Porter 1980). In contrast, in markets where the competition level is low, incumbents typically enjoy large market shares and a high profit margin, making competition with such incumbents tough, especially for startups. That is, different market structures pose different challenges for startups when entering new markets. Furthermore, as noted by Sutton (1998), in markets where the competition level is high, consumer preferences are typically relatively homogeneous, so a major innovation can increase market share dramatically. In contrast, in markets where the competition level is low, consumer preferences typically widely differ or there is low substitutability among products; as a result, a profound increase in market share is much less likely. It is, therefore, plausible that there are distinguishable differences in the incentives of startups and incumbents to cooperate at different levels of market competition, and that those incentives will be differently influenced by the level of innovativeness of startups' products.

In order to study these differences, we analyze a novel data set of 93 high-technology Israel-based startups operating in a wide range of high-tech markets. We focus on the entry mode of these startups into the U.S. market—the main market of these startups. We evaluate whether the propensity of the startups to cooperate with U.S.-based incumbents in commercializing their innovations is affected by the level of competition in the relevant U.S. markets, and by the interaction of these markets' competition level with the startups' level of innovativeness.

We find that the propensity of startups and incumbents to cooperate is nonmonotonic in the level of market competition; it initially decreases with the level of competition and then increases with it. Interestingly, we find that the effect of startups' degree of innovativeness on the propensity to cooperate with market incumbents is contingent on competition level. Greater startup innovativeness decreases the propensity of cooperation in U.S. markets with high competition level, but increases it in markets with low levels of competition.

What drives these differences in startup-incumbent cooperation propensity at different levels of market competition? In general, cooperation induces three main effects: (1) Cooperation generates additional value as startups gain access to incumbents' complementary assets, reputation, and superior brands. We refer to this effect as the *revenue expansion effect*. (2) Under cooperation, startups must share revenues with the market incumbents, while under competition, they keep all revenues to themselves. We call this the *revenue sharing effect*. (3) Cooperation entails an increase in the probability of imitation (Gans and Stern 2003, Khanna et al. 1998, Hsu 2006). We label the overall risk of imitation by incumbents the *imitation effect*. It is the interaction of these three effects that determines firms' propensity to cooperate. Our results are consistent with the contention that these three effects vary both with competition level and with the level of startups' innovativeness. In markets with either a high or low level of competition, the benefits for startups of cooperation (revenue expansion effect) outweigh the costs of cooperation (revenue sharing and imitations effects). However, in markets with a moderate level of competition the revenue expansion effect is relatively modest, while the revenue sharing and imitation effects peak, significantly reducing the benefits for startups from cooperation relative to their potential benefits from competition.

The contingent effect we find for innovativeness suggests that greater startup innovativeness plays a dual role. Greater innovativeness likely increases the complexity of the startup's technology and thus reduces the imitation effect. Furthermore, greater innovativeness likely increases the value of the startups' products to consumers, and thus startups' bargaining power (Gans et al. 2002, Trajtenberg 1990), thereby decreasing the revenue sharing effect. While the decrease in the imitation effect increases the startup's benefits from competing in the market, the decrease in the revenue sharing effect makes cooperation more lucrative. Which effect dominates then depends on the competition level. In markets with a high level of competition, the decrease in the imitation effect dominates the revenue sharing effect, and thus greater innovativeness in such markets decreases the propensity of startup-incumbent cooperation. In markets with a low level of competition, decreased threat of imitation may not suffice to induce startups to compete, as incumbents' dominance in the market greatly increases the revenue expansion effect. In such markets, startups will prefer to make use of their increased bargaining power (resulting from their greater innovativeness) to decrease the revenue sharing when cooperating with incumbents.

We address selection and endogeneity concerns (Shaver 1998) with multiple empirical vehicles, including firm fixed effects, Coarsened Exact Matching analysis, and Arellano–Bond's generalized method of moments estimation (Angrist and Pischke 2008, Arellano and Bond 1991, Iacus et al. 2012). The high consistency of results across all alternative approaches grants confidence in the validity of our findings.

Our setup of the entry of high-tech Israeli startups into U.S. high-tech markets, where they are typically unknown to customers and do not possess the required complementary assets, offers a relatively clean examination of how the tension between the technological superiority of startups relative to their inferiority in complementary assets, brand recognition, and reputation affect startup-incumbent cooperation propensity. Indeed, this setup also informs the vast foreign market entry literature (e.g., Agarwal and Ramaswami 1992, Anderson and Gatignon 1986, Brouthers 2002, Buckley and Casson 1998, Hennart 1988, Hill et al. 1990), and in particular, studies concerning the entry of startup firms into foreign markets soon after their inception (Hashai 2011, Zahra et al. 2000). This literature typically builds on transaction costs economics (TCE) and resource based view (RBV) reasoning, but has paid scant attention to the role of the level of competition in foreign markets in shaping foreign market entry modes. We contribute to this strand in the literature by explicitly considering the effect of competition, as well as its interaction with the startups' innovativeness.

The remainder of this paper is organized as follows: First, we discuss the two market entry modes and their associated costs and benefits. An empirical analysis of the entry modes of Israeli high-tech startups into a wide range of U.S. markets, varying in their competition levels, follows. Finally, we discuss the possible implications of our results and their limitations, and highlight avenues for further research.

Startups' Market Entry Modes

Our analysis focuses on innovative high-tech startups that are likely to be inferior to market incumbents in terms of their complementary assets, brand recognition, and reputation, due to their age, size, and overall knowledge of the market (Rothaermel 2001, Singh and Mitchell 2005, Teece 1986). In general, innovative startups can take two distinct approaches for market entry: (1) compete head-on with market incumbents; or (2) cooperate with market incumbents by licensing out their technological innovation or engaging in strategic alliances. Such cooperation allows taking advantage of the superior complementary assets of market incumbents in terms of production sites, marketing facilities and distribution channels, superior market knowledge, brand recognition, reputation, and customer loyalty (Rothaermel 2001, Singh and Mitchell 2005, Teece 1986). The emergence of either market entry mode depends, to a large extent, on the value that startups' innovations create and the share of this value that startups and market incumbents are able to capture as profits (Porter 1980, Pisano 1990, Teece 1986).

Startups and market incumbents will collaborate only if both are able to capture additional value from cooperation, compared with directly competing in the marketplace. The extant literature suggests that startups should possess substantial complementary assets to directly compete when entering a new market (Chen and Hambrick 1995, Gans and Stern 2003, Teece 1986), and that the possession of strong intellectual property rights (IPR) protection further pushes startups to compete with incumbents (Arora and Ceccagnoli 2006). Cooperation with market incumbents may allow startups that do not possess such assets to better reach the potential market during their early years of market entry. The benefits of a larger revenue potential from cooperation, however, come at a cost as the startups must share sales revenues with the incumbents. In addition, TCE reasoning suggests that cooperation increases the probability that market incumbents would imitate the newly introduced products (Anderson and Gatignon 1986, Gans et al. 2002, Teece 1986, Williamson 1985). Indeed, imitation by means of reverse engineering is also possible in the case where startups and market incumbents compete. In the case of cooperation, however, imitation may result from unintended disclosure (Arora et al. 2001) in addition to reverse engineering, making imitation under cooperation more probable than imitation under competition (Gans et al. 2002, Khanna et al. 1998).

From the incumbents' point of view, cooperation with startups allows offering technologically superior products in the market, while using their complementary assets more efficiently and reinforcing their brand recognition and reputation (Singh and Mitchell 2005). Furthermore, incumbents often choose to cooperate with startups to learn about the specifications of new technologies and, in turn, develop and sell such innovations on their own (Baum et al. 2000, Kale et al. 2000, Khanna et al. 1998, Rothaermel 2001). Furthermore, as suggested by Brandenburger and Nalebuff (1996), startups and incumbents may cooperate to take advantage of each other's strengths, but still also take advantage of each other's weaknesses to better compete in the market.

The economic value created by a startup's innovation varies widely, and crucially depends on the quality of the innovation brought to the market (Lanjouw and Schankerman 2004). In general, two main drivers determine the quality of an innovation: the willingness of consumers to pay, which is often driven by the degree of innovativeness of the product; and the strength of IPR protection it provides, due to technological complexity that makes imitation hard (Harhoff et al. 2003, Lerner 1994, Reitzig and Puranam 2009, Trajtenberg 1990). Competition level then limits the value that the startup can capture as profits.

Importantly, it is noteworthy that startups' market entry is a long process with short run and long run effects. In the short run, when startups are in their early years of operation, they are too small to affect competition level in terms of market shares and firm dominance. Incumbents, thus, typically initially respond to such entry with price reductions and imitation attempts. In the long run, depending on the degree of startup innovativeness and the incumbents' position in the market, one may expect to see distinct changes in competition level. We focus in our analysis on startups' early years of operation where the effect of the startup's entry mode on the overall level of market competition is likely negligible. If a given startup competes with incumbents, it is usually a very small market player, while if it collaborates with incumbents, its innovation is assumed to replace that of the incumbents.

In the Regression Analysis section, we empirically examine whether the ability of startups and market incumbents to capture the value of an innovation varies across markets with a high level of competition and markets with a low level of competition. While in the former, market shares and profit margins are typically small and hard to sustain, in the latter, incumbents dominate and typically enjoy large market shares and a high profit margin (Porter 1980). We then examine whether and how startups' level of innovativeness influences this variation.

Data

Sample

To test the relationship between competition level, startup innovativeness, and the propensity of startup-incumbent cooperation, we study a sample of Israel-based high-tech startups entering different U.S. markets. The high-tech sector is a suitable setting for the current research since technological innovation, often sparked by startups, is a key characteristic of this sector (Teece 1986). Given that Israel has a very small home market, for most Israeli high-tech startups, the

U.S. market is the primary target market to which such startups enter soon after their inception (Senor and Singer 2009). In fact, about 66% of the revenues of the sampled firms are obtained in this market.[1] This setting allows us to track the entry mode of startups in terms of their propensity to cooperate or compete with U.S. market incumbents in the commercialization of their technological innovations in their early years of market penetration. It allows us to examine how startups that are often unknown to customers, and do not possess the required complementary assets, enter markets where incumbents typically possess significant complementary assets, brand recognition, and reputation. Our data set is comprised of industries with varying degrees of competition. The ability to match data concerning the entry strategies of startups in their early years of market entry with information on competition level at the six-digit North American Industrial Classification System (NAICS) level allows us to test the relationships between competition level, startup innovativeness, and the propensity of startup-incumbent cooperation.

The sample was derived from a full list of Israel-based high-tech startups constructed by the Dolev and Abramovitz Ltd. consulting firm for the year 2007. Dolev and Abramovitz Ltd. is a private company that collects and publishes annual information on Israeli high-tech startups, and its data set is well-recognized as a comprehensive resource for this sector in Israel. The data set includes 408 startups that have reached the stage where they already sell their products or services, which allows us to observe the extent to which these startups choose to cooperate or compete with incumbents in their early years of entry into different U.S. markets.

Firm-level data, including revenues, number of employees, firm age, and attracted investments, were collected from the Dolev and Abramovitz data set and the Israel Venture Capital (IVC) data set. The IVC data set is another comprehensive source for Israeli high-tech startups.[2] Using annual financial reports and prospectuses, additional financial data such as R&D expenses were collected. These data are readily available for public firms, and we were granted access to key figures in the financial reports of private firms (representing 72% of our sample). We also collected patent and patent citations data for the sample firms from the United States Patent and Trademark Office.

Data on industry measures such as value added, revenues, capital intensity, advertising intensity, and industry concentration were taken from the U.S. Census Bureau (part of the U.S. Department of Commerce) and are available as part of the economic censuses for 2002 and 2007. These data are at the six-digit NAICS level. They refer to the core industry code of each start-up firm[3] and are available only to the manufacturing sector (i.e., industries belonging to the 31–33 two-digit NAICS range).

Additional data that were unavailable from secondary sources were collected through a personal survey based on structured questionnaires with senior management at each surveyed startup. We randomly selected 150 high-tech startups, and members of the top management team were asked to participate in a personal survey. Senior representatives of 124 of these startups agreed to participate in the survey, and interviews by means of a structured questionnaire were conducted by one of the authors and a small group of graduate students.[4] The interviews took place with two to three senior managers whose replies were triangulated to ensure consistency. The interviewees were typically chairpersons, CEOs, or senior vice presidents (VPs) who had sufficiently long tenure with the startup to be able to effectively reflect on the startup's history, as well as have access to supporting formal documentation.[5] The questionnaires covered a wide range of "hard data," on an annual basis, including: the extent of independent and collaborative sales; number of R&D, manufacturing, and distribution employees; and the number of product models each firm has within its core industry. These data were tested against multiple secondary sources to the greatest possible extent.

Of the 124 startups, we screened out 14 startups whose interviewees supplied incomplete data. Five more startups were screened out for being substantially larger and older than the other firms. Finally, 12 startups did not report any operations in the U.S. market, and hence were also screened out. This resulted in a sample of 93 startups. T-test comparisons between the 93 participating startups and the 315 nonparticipating startups show no evidence of any nonresponse bias in terms of the averages of firm sales, number of employees, firm age, firm valuation, and industrial classification (at the six-digit NAICS level). Overall, this procedure resulted in an unbalanced panel data set of 560 firm-year observations for the 93 analyzed startups within the period 2000–2007. These firms operate in 33 high-technology NAICS sectors, such as printing machinery and equipment, semiconductor machinery, optical instruments and lens, telephone apparatus, radio and television broadcasting equipment, wireless communications equipment, semiconductors and related devices, electronic components, electro-medical apparatus, electrotherapeutic apparatus, surgical instruments, and medical instruments.

Key Variables

Our three key variables are the propensity of cooperation, degree of innovativeness, and competition level. As a proxy for the propensity of cooperation, we take the annual ratio of each startup's U.S. market sales, derived from either licensing or commercialization alliances with U.S. incumbents selling competing products, minus costs, to the startup's overall sales minus overall costs.[6] This measure represents the share of profits that each startup derives through collaborative sales with local incumbents out of its overall profits in the United States. We denote this measure as *cooperation propensity*.

The logic behind this measure is to identify the dominant mode generating profits for the startups in our sample. Indeed, 82% of the startups in our sample obtain their profits predominantly from either cooperation or competition (i.e., more than 75% of their profits in a given year come from either competition or cooperation), while only 18% of the startups have more balanced profits (i.e., more than 25% of their profits come from one mode while the rest come from the other mode).

We use industry level value added to revenues ratio as a proxy for *competition level*—the higher the ratio, the lower the level of competition in the market.[7] Specifically, we measure the value added to revenues ratio of specific U.S. six-digit NAICS industries by dividing industry value added by industry level revenues.[8] Value added is the best measure available for comparing the relative margins of different manufacturing industries. The data reported by the U.S. Census Bureau are available as part of the economic censuses for 2002 and 2007. We make the assumption that value added data are unlikely to change drastically within a two-year interval. As such, data referring to 2002 were assigned the years 2000–2004 *competition level* measures and 2007 data were assigned the 2005–2007 *competition level* measures. While making such an assumption is not ideal, we are constrained by the census frequency that takes place only every five years.

In order to be able to capture the different aspects of innovativeness, we use two measures for the degree of startups' innovativeness. The first is a dummy variable, receiving a value of 1 if a given startup's R&D expenses in a given year exceed the average R&D expenses of all other sample startups belonging to the same six-digit NAICS code, and a value of 0 otherwise. We denote this measure *innovativeness*, and it is expected to reflect the level of the startup's innovation relative to other startups in its industry.[9] The second is the weighted number of patent citations for patents filed by a startup in the United States, up to each year. Following Trajtenberg (1990), we weigh each patent by the number of citations it has received plus one (as a means to count the patent itself if it has no citations), and sum up these weights for all patents filed up to a given year. We denote this measure *weighted patent citations*. The measure does not only reflect the economic value of patents (Harhoff et al. 2003, Lerner 1994, Trajtenberg 1990), but also the propensity of startups to protect their technology through patents and the strength of such patent protection. Patent citation often indicates the failure of rival firms to bypass the protection granted by patents, requiring them to cite patents and subsequently pay for the use of such patents (Lerner 1994, Reitzig and Puranam 2009). Patent citations therefore "represent a limitation on the scope of property rights established by the patent's claims, which carry weight in court" (Trajtenberg 1990, p. 174). A higher number of patent citations, therefore, likely exhibits a relatively higher ability of startups to capture the value of their technological innovations when they either compete or cooperate (Cohen et al. 2000, Gans et al. 2002, Teece 1986). This measure displays high levels of skewness and is therefore log-transformed.

Descriptive statistics and correlations are presented in Table A.1 in the appendix. The startups in our sample are young yet fairly established (about five years old) and small to medium-sized in terms of revenues (under $US 20 million in the United States, and total sales of about $US 30 million). On average, the startups in the sample have entered the U.S. market about two years after their inception, and our data captures their first years of market entry. The startups in the sample have, on average, 32 citations per patent, but variance is high. On average, a startup has 3.85 cooperation agreements with U.S. industry incumbents (with a maximum of 21). Our sampled startups demonstrate a nice variance in their entry modes and the analyzed six-digit NAICS sectors also vary substantially, mainly in terms of the market value added to revenues ratio (reflecting competition level) and capital intensity.

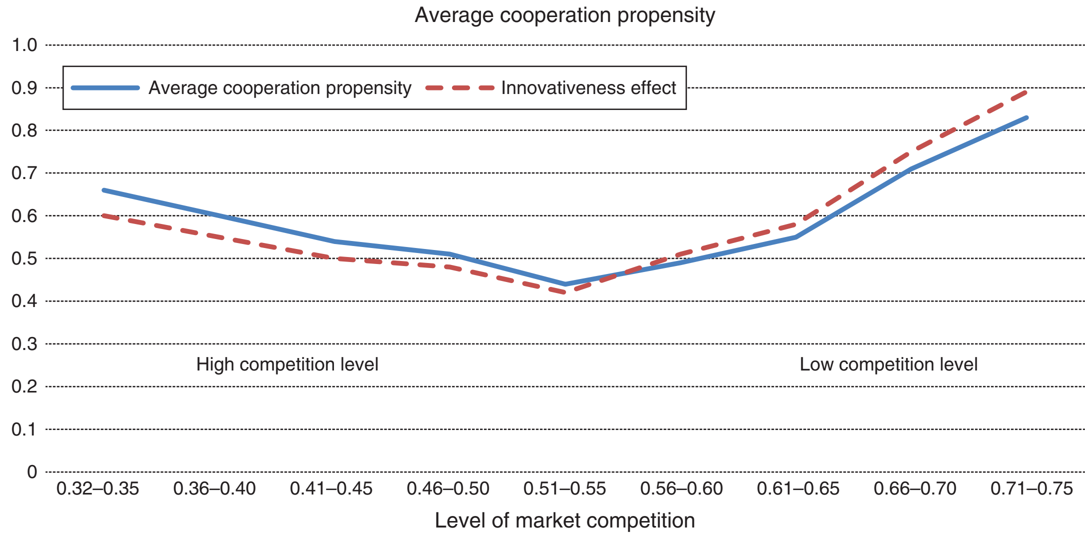
Empirical Strategy and Analysis

We start our analysis by plotting the average cooperation propensity of the startups in our sample over the corresponding competition level (starting at the minimal competition level in steps of 0.05). Figure 1 plots the overall average cooperation propensity (solid line) as well as the average cooperation propensity of startups whose *innovativeness* measure equals one (dashed line); i.e., more innovative startups. Both graphs strongly suggest a U-shape relationship with a minimum at moderate levels of market competition. Interestingly, the cooperation propensity of more innovative startups, as compared to the average startup in our data, is lower in markets with high levels of competition, yet higher in markets with low competition levels. We further support these basic findings with the regression analyses below and propose some intuition for it in the Discussion section.

Regression Analysis

To test the relationship between competition level and cooperation propensity, we first run ordinary least squares (OLS) regressions of our measure for startups-incumbents cooperation on our measures of competition level, innovativeness, and control variables. Given

Figure 1. (Color online) Competition Level and Cooperation Propensity



the U-shape relationship evident in Figure 1, we subdivide our competition level variable and define four binary measures representing four quartiles of competition levels in each year: *competition level* ith *quartile*, $i = \{1, 2, 3, 4\}$. For example, *competition level* 1st *quartile* takes on the value of 1 for startups operating at the lowest 25% of the market value added to revenues ratio, and 0 otherwise. The direction and significance of the *differences* between the coefficients on these competition level quartile measures is used to determine the overall pattern of the competition level-cooperation propensity relationship.

Control Variables. In our analysis, we control for multiple factors at the industry and firm level that are likely to affect cooperation propensity.

At the industry level, we control for *advertising intensity* measured by the costs of advertising and promotional services divided by industry revenues. We further control for *capital intensity* measured by the gross value of depreciable assets at end of year divided by industry revenues. These data are reported by the U.S. Census Bureau as part of the economic censuses for 2002 and 2007. We have assigned data referring to 2002 to the years 2000–2004, and data referring to 2007 to the years 2005–2007. Both of these industry level measures serve as proxies for the strength of specialized complementary assets (Arora and Ceccagnoli 2006, Teece 1986) required at each industry, and hence are likely to affect the cooperation propensity of startups. Furthermore, both advertising and capital intensity are exogenous drivers of market structure (Sutton 1991), and thus can be used to estimate changes in competition level.

At the firm level, firms with higher revenues are likely to have a higher propensity to compete rather than cooperate. Therefore, we control for startups' overall revenues in the United States via the logarithmic transformation of revenues (Ln_*revenues*).[10] We further use the *number of VCs* investing in a given startup (in multiple investment rounds) up to a given year as a proxy for the effect of venture capital funds (VCs) presence on transaction costs. VCs that back startups are often instrumental in reducing transaction costs under cooperation, such as search and negotiation costs, for example, for both the startups and incumbents. VCs can reduce transaction costs through their involvement in negotiations and because they often provide a positive reputation signal for the startups (Gans et al. 2002, Gans and Stern 2003, Hsu 2006). Following this reasoning, a higher number of VCs who invest in a given startup indicates greater potential for reducing transaction costs, and hence may increase the propensity of startup-incumbent cooperation.[11]

Next, we control for the possession of complementary assets by startups. We measure the startups' *complementary assets* by the number of manufacturing and distribution employees employed each year (Colombo et al. 2006, Rothaermel and Hill 2005). This measure was heavily skewed and thus log-transformed. The extent to which a startup can build its own independent manufacturing and distribution often reflects the extent to which it possesses complementary assets (Cohen et al. 2000, Nerkar and Shane 2003, Teece 1986) which, in turn, may decrease its propensity to cooperate.

We also control for the total value of *investments* (in $US Millions) made in each startup via private investors, VCs, corporate venture capital, acquisitions, and/or public offerings. Such investments may affect the ability of startups to compete in their markets, as they positively influence the ability of startups to build complementary assets. Because investments are heavily skewed, we use a logarithmic transformation.

We further control for the number of *product models* of each startup by counting the cumulative number of product lines that a startup has in a given year. We expect startups with more product models to have a higher propensity to cooperate with incumbents, due to the need to use multiple kinds of complementary assets. Finally, we also control for startup *age*.

OLS Regression. We run OLS models both for the whole period (2000–2007) and only for the years 2002 and 2007, for which we have complete data on competition level. In addition, we also run firm fixed effects models, as means to control for time invariant unobservable firm-specific characteristics that may affect the propensity to cooperate (Campa and Kedia 2002).

Table 1 presents these regressions' estimates. We include two sets of regressions, one with *weighted patent citations* and one with *innovativeness* as proxy for startups' innovativeness:

$$\begin{aligned} &\textit{Cooperation propensity}_{jt} \\ &\quad = \sum_{i=2}^{4} \alpha_i \textit{Competition level } i\text{th } \textit{quartile}_{jt} \\ &\qquad + \beta \textit{ Weighted patent citations}_{jt} \\ &\qquad + \sum_{i=2}^{4} \gamma_i \textit{Weighted patent citations}_{jt} \\ &\qquad \times \textit{competition level } i\text{th } \textit{quartile}_{jt} + \lambda X_{jt} + \varepsilon_j, \\ &\textit{Cooperation propensity}_{jt} \\ &\quad = \sum_{i=2}^{4} \alpha_i \textit{Competition level } i\text{th } \textit{quartile}_{jt} \\ &\qquad + \beta \textit{ Innovativeness}_{jt} + \sum_{i=2}^{4} \gamma_i \textit{Innovativeness}_{jt} \\ &\qquad \times \textit{competition level } i\text{th } \textit{quantile}_{jt} + \lambda X_{jt} + \varepsilon_j, \end{aligned}$$

where j, t, and i index startups, time, and quartiles, respectively; X_{jt} represents the vector of control variables for startup j at time t; and ε_j is the error term. The coefficients on γ_i are our coefficients of interest.

Model 1 in Table 1 is our baseline OLS model without interactions. Models 2–4 include interactions of the three competition level quartile dummies with *weighted patent citations*, while models 5–7 include the same estimations with interactions of competition level quartile dummies with *innovativeness*.[12] For each measure of innovativeness, we present the results for a simple OLS regression (models 2 and 5), a fixed effects OLS estimation (models 3 and 6), and since most of our variation is cross sectional, an OLS estimation for the years 2002 and 2007, resulting in a subsample of 186 firms (models 4 and 7).

The results of all models are quite consistent. Startups in the *competition level* 2nd *quartile* are about 7.5%–13% less likely to cooperate than startups belonging to the *competition level* 1st *quartile*. Startups in the *competition level* 3rd *quartile* are 9%–12% less likely to cooperate than startups in *competition level* 1st *quartile*. For startups in the *competition level* 4th *quartile*, the coefficient flips and becomes positive, resulting in about 2%–3% higher likelihood to cooperate than startups in *competition level* 1st *quartile*. Wald tests confirm that the coefficients on *competition level* 4th *quartile* are significantly larger than those on *competition level* 3rd *quartile* ($p > F = 0.000$). Taken together, these results are consistent with the U-shaped relationship shown in Figure 1, suggesting that startups in our sample are more likely to cooperate in markets with high or low competition levels as opposed to markets with moderate competition levels.

Table 1 further reveals that the main effect of *weighted patent citations* on *cooperation propensity* is negative, suggesting that, in general, startups with strong innovation and strong patent protection are less likely to cooperate. This effect, however, varies with competition level. Specifically, we find that at moderately high levels of competition level (*competition level* 2nd *quartile*), a larger number of patent citations reduces the propensity to cooperate by between 8.5% and 10.5%. On the other hand, at moderately low levels of competition (*competition level* 3rd *quartile*), having more patent citations significantly increases *cooperation propensity*. Interestingly, a larger number of patent citations increases *cooperation propensity* even more at low levels of competition (i.e., *competition level* 4th *quartile*).[13]

A similar story is revealed when studying the effects of *innovativeness* on *cooperation propensity*. That is, larger-than-industry-average investments in R&D increase the propensity to cooperate in markets with low competition levels, yet decreases it in markets with high competition levels. Taken together, these results suggest that the effect of a more progressive, complex, or harder-to-imitate innovation on the propensity to cooperate is contingent on the level of competition. At high to moderately-high levels of competition, higher quality technological innovations (in terms of *weighted patent citations* and *innovativeness*) reduce *cooperation propensity*. In contrast, at moderately-low to low levels of competition, higher quality innovations increase *cooperation propensity*.

As expected, being supported by a larger number of VCs is positively correlated with *cooperation propensity*, while having strong *complementary assets*, or being larger in term of revenues (Ln_*revenues*) decrease the propensity to cooperate. Likewise, operating in a high *capital intensity* industry reduces *cooperation propensity*. No significant correlations are found between *advertising intensity*, *investments*, *product models*, or *age*, and *cooperation propensity*. In terms of industry effects, results (not reported in Table 1) show that there is still some unobserved heterogeneity across industries

Table 1. Competition Level and Cooperation Propensity—Ordinary Least Squares (OLS) Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable—Cooperation propensity	Baseline OLS	OLS	OLS (firm FE)	OLS (2002, 2007)	OLS	OLS (firm FE)	OLS (2002, 2007)
Competition level 2nd quartile	−0.109*	−0.102*	−0.075*	−0.131**	−0.099*	−0.079*	−0.129**
	(0.049)	(0.045)	(0.036)	(0.036)	(0.042)	(0.035)	(0.041)
Competition level 3rd quartile	−0.092*	−0.095*	−0.088*	−0.119**	−0.089*	−0.092*	−0.116**
	(0.040)	(0.042)	(0.042)	(0.033)	(0.038)	(0.038)	(0.038)
Competition level 4th quartile	0.035*	0.033*	0.021*	0.032*	0.042*	0.030*	0.025*
	(0.017)	(0.013)	(0.091)	(0.15)	(0.020)	(0.014)	(0.11)
Weighted patent citations	−0.050*	−0.036*	−0.044*	−0.045*	−0.056*	−0.058*	−0.044*
	(0.023)	(0.017)	(0.022)	(0.023)	(0.022)	(0.024)	(0.021)
Weighted patent citations × Competition level 2nd quartile		−0.106**	−0.086*	−0.103**			
		(0.035)	(0.037)	(0.031)			
Weighted patent citations × Competition level 3rd quartile		0.089**	0.065*	0.082*			
		(0.030)	(0.032)	(0.037)			
Weighted patent citations × Competition level 4th quartile		0.197*	0.178*	0.188*			
		(0.099)	(0.088)	(0.083)			
Innovativeness	−0.039*	−0.044*	−0.035*	−0.041*	−0.029*	−0.031*	−0.035*
	(0.018)	(0.022)	(0.016)	(0.019)	(0.013)	(0.014)	(0.016)
Innovativeness × Competition level 2nd quartile					−0.046*	−0.043*	−0.051*
					(0.021)	(0.017)	(0.021)
Innovativeness × Competition level 3rd quartile					0.077*	0.069*	0.085*
					(0.032)	(0.028)	(0.035)
Innovativeness × Competition level 4th quartile					0.105*	0.084*	0.087*
					(0.048)	(0.039)	(0.039)
Advertising intensity	−0.140	−0.143	−0.121	−0.120	−0.138	−0.119	−0.115
	(0.081)	(0.086)	(0.092)	(0.085)	(0.089)	(0.090)	(0.073)
Capital intensity	−0.198*	−0.205*	−0.161*	−0.209**	−0.223*	−0.150*	−0.199*
	(0.093)	(0.101)	(0.070)	(0.065)	(0.094)	(0.071)	(0.089)
Ln_revenues	−0.168**	−0.176**	−0.113*	−0.124**	−0.167**	−0.107*	−0.119**
	(0.047)	(0.051)	(0.052)	(0.040)	(0.055)	(0.046)	(0.038)
No. of VCs	0.089*	0.083*	0.025*	0.093*	0.087*	0.029*	0.090*
	(0.038)	(0.036)	(0.012)	(0.042)	(0.032)	(0.014)	(0.037)
Complementary assets	−0.106*	−0.110*	−0.057*	−0.118*	−0.105*	−0.052*	−0.122*
	(0.052)	(0.055)	(0.029)	(0.057)	(0.051)	(0.022)	(0.056)
Investments	0.019	0.017	0.009	0.028	0.021	0.019	0.027
	(0.021)	(0.020)	(0.011)	(0.019)	(0.020)	(0.013)	(0.014)
Product models	0.118	0.123	0.035	0.118	0.135	0.045	0.102
	(0.090)	(0.093)	(0.026)	(0.081)	(0.103)	(0.029)	(0.088)
Age	0.120	0.125	—	0.123	0.119	—	0.117
	(0.101)	(0.099)		(0.090)	(0.092)		(0.095)
Industry fixed effects	+	+	—	+	+	—	+
Year fixed effects	+	+	+	+	+	+	+
No. of firm-year observations	560	560	560	186	560	560	186
R squared	0.19	0.23	0.21	0.28	0.21	0.20	0.27

Notes. Robust standard errors in brackets. Constants not reported.
**Statistically significant at 1%; *statistically significant at 5%.

where *cooperation propensity* is significantly higher in the semiconductor machinery, semiconductor, storage device manufacturing, and medical instruments industries; and significantly lower in the optical instrument and lens industry.

Selection Bias and Endogeneity

Our OLS analysis is prone to two possible statistical biases. One bias concerns selection in the industrial distribution of startups. In other words, it is possible that startups that operate in six-digit NAICS industries characterized by different levels of competition systematically differ in other parameters. If this is indeed the case, one may attribute the propensity to cooperate with market incumbents to the level of competition, whereas, in fact, such propensity may result from other differences in the attributes of startups.

The second potential bias is endogeneity. While market choice is often determined by the nature of startups' technologies, to the extent that startups can select the markets (industries) in which they wish to operate, market choice and the market competition level may be endogenous to a startup's cooperation propensity (Shaver 1998). For example, one may argue that startups with fewer resources may prefer to choose markets where there are more cooperation opportunities. In such a case, it would be the desire to cooperate that dictates market choice, rather than competition level dictating the propensity to cooperate. In addition, weighted patent citations and the level of innovativeness may reflect startups' ex-ante preference to compete rather than cooperate. Moreover, startups' complementary assets are also likely to be endogenous to the propensity to cooperate (Teece 1986), where startups that prefer to compete would invest more in complementary assets.

To account for the potential selection bias in our data set, we employ a coarsened exact matching (CEM) estimation. To try and deal with the endogeneity bias, we complement our analyses with the generalized method of moments introduced by Arellano and Bond (1991).

Matching. Matching treatment and control groups on relevant observable characteristics is likely to mitigate selection bias concerns as it creates a subsample of comparable firms. Propensity score matching (Rosenbaum and Rubin 1983) is often a popular procedure among strategy scholars for estimating the influence of noncomparable control and treatment group observations that are off the common support of an estimated propensity score distribution and allows for the elimination of incomparable observations (e.g., Chang et al. 2013, de Figueiredo et al. 2013, Leone and Reichstein 2012, Rawley and Simcoe 2010). Yet, recent studies (Blackwell et al. 2009, Iacus et al. 2012, King et al. 2011) suggest that propensity score matching (PSM) may, in fact, degrade inferences relative to not matching at all, and that CEM is likely to produce matched samples that are more balanced. CEM also assures that adjusting the imbalance on one variable has no effect on the maximum imbalance of any other variable. We have therefore followed several other strategy scholars that have adopted CEM (e.g., Aggarwal and Hsu 2014, de Figueiredo et al. 2013, Feldman et al. 2016) and confine PSM to the robustness analysis. The CEM algorithm performs exact matching on coarsened data to determine matches between control and treatment groups. Exact matching is conducted by sorting all the observations into strata, each of which has identical values for all the coarsened pretreatment covariates, and then discarding all observations within any stratum that do not have at least one observation for each unique value of the treatment variable. While CEM is not expected to control for all unobservable differences between firms, it mitigates selection effects by reducing the *observable* differences between treatment and control groups.

In our CEM model, a first-stage regression is fitted to estimate the probability of startups for being "treated" by a decrease in competition level, and those that are a control group. We do this by choosing a type of coarsening for all of our covariates. We have experimented with several coarsening alternatives in order to minimize the imbalance between our control and treatment observations. The best coarsening strategy (i.e., the one minimizing sample imbalance) was achieved when industry is coarsened into four digit NAICS groups (allowing us to have treatment and control observations from similar industries). Innovativeness is coarsened into two groups (above and below average R&D expenditures in the industry), and the remaining covariates (*Weighted patent citations, Advertising intensity, Capital intensity, Ln_revenues, No. of VCs, Complementary assets, Investments, Product models*, and *Age*) are coarsened into quartiles based on their distributions.[14] Since CEM does not require a one-to-one matching between control and treated observations, control observations within each stratum are weighted to equal the number of treated observations in that stratum.[15] The predicted propensities of startups to incur a decrease in competition level, as derived from the output of the coarsened first-stage regression, are then incorporated into a second-stage regression estimating startups' cooperation propensity. The inclusion of uncoarsened values of the independent variables in the second-stage regression accounts for any remaining imbalance in the sample.

GMM Analysis. Ideally, we would like to use instrumental variables to control for potential endogeneity as previously discussed, as often done in strategy research (e.g., Hashai 2015, Shaver 2005, Simsek et al. 2007).[16] Unfortunately, we could not identify strong instruments for our sample, specifically given that we face multiple endogenous relationships among our variables.[17] We have therefore followed Dezső and Ross (2012), Gedajlovic and Shapiro (2002), Suarez et al. (2013), Uotila et al. (2009), and other strategy scholars, and use the generalized method of moments (GMM) introduced by Arellano and Bond (1991) to estimate our regression models, thus applying panel random-effect methods. To do this, we first take differences in our dependent and independent variables to control for unobservable model-specific effects. Arellano and Bond (1991) show that the most efficient set of instruments, in the absence of serial correlation, are the lagged values of the dependent variable and the potentially endogenous explanatory variables (i.e., *competition level*, *weighted patent citations*, *innovativeness*, *No. of VCs*, and *complementary assets*) from $t-2$. We adopt these instruments in our GMM models. In addition, building on the work of Arellano and Bover (1995), who use two years lagged differences as potential additional instruments, Blundell and Bond (1998) exploit additional moment restrictions, which substantially improve the performance of the Arellano and Bond GMM estimator in circumstances where the number of time-series observations is relatively small (e.g., when there are relatively few years of data). Given that we have a maximum of eight periods per firm (2000–2007), we adopt the Blundell and Bond (1998) extension and include two years lagged differences of the dependent variable and the potentially endogenous explanatory variables as additional instruments to improve our estimates.

In Table 2, we present our CEM and GMM regressions estimates for the models we ran in Table 1. The CEM models include 494 firm-year observations out of the original 560 observations, as a second stage of the first stage coarsened exact matching model detailed in Table A.2 in the appendix.[18] Reassuringly, the results of the models presented in Table 2 are highly consistent with those presented in Table 1. The GMM models provide support for our specifications in terms of their Wald statistics, and the Sargan tests (Sargan 1988, Blundell and Bond 1998) confirm the validity of the instruments. The null hypothesis of no serial autocorrelation of the residuals is also accepted.

An Alternative Approach

To further study the relationship between cooperation propensity and levels of competition, we run difference-in-differences treatment models. Difference-in-differences (hereafter DID) treatment integrates the advances of the fixed effects estimators with a causal inference analysis when unobserved events or characteristics may confound interpretations (Angrist and Pischke 2008). Here we use the DID analysis to see whether a considerable decrease in the level of competition affects startups that operate in markets with a high level of competition differently (in terms of their cooperation propensity) than those operating in markets with a low level of competition. Since we are only looking at substantial decreases in competition, we think of these as exogenous shock. Consequently, such a test may serve as an appealing experiment to further tease out the relationships between cooperation propensity and the level of competition.

Difference in Differences Analysis. Our DID approach divides the industries in our sample into six-digit NAICS industries with 2002 competition-level measures below the average competition level of our sample, and six-digit NAICS industries with 2002 competition level measures above the average competition level.[19] In our sample, 51 startups operated in 2002 in a market with high competition levels (reflected by low market value added to revenues ratio), while 42 operated in markets with a relatively low level of competition (reflected by high market value added to revenues ratio). Based on our OLS regressions results, one would expect that a decrease in the level of competition would have a different effect on the propensity of startups to cooperate in these two different sets. To this end, we define a binary treatment measure as follows:

$$\textit{Decrease in competition level}_{jt} = \begin{cases} 1 & \dfrac{\textit{market value added}}{\textit{market revenues}}, \quad \textit{increased by } 10\% \textit{ or more between } 2002 \textit{ and } 2007; \\ 0 & \textit{otherwise}. \end{cases}$$

This measure reflects whether startups have experienced a decrease in competition level. In the regression analyses, we test whether startups that operated in 2002 in a high competition market and experienced a decrease in competition level exhibit a significantly different propensity to cooperate relative to startups that operated in 2002 in a market with high competition, but did not experience a decrease in competition level. We then repeat this test for startups that operated in 2002 in low competition markets. We further test whether the effect of *weighted patent citations* and *innovativeness* on startups that experienced a substantial decrease in competition level between 2002–2007 is different for startups that operated in 2002 in high competition markets than for those that operated in low competition markets.

In our DID analysis, we use only observations for 2002 and 2007 (i.e., two observations per firm) and perform the following estimation:

$$\begin{aligned} &\textit{Cooperation propensity}_{jt} \\ &\quad = \alpha\, \textit{Year}_{jt} + \beta\, \textit{Decrease in competition level}_{jt} \\ &\qquad + \delta\, \textit{Year}_{jt} \times \textit{Decrease in competition level}_{jt} + \gamma X_{jt} + \varepsilon_j, \end{aligned}$$

where, as before, j and t index startups and time, respectively; X_{jt} represents the vector of control variables for startup j at time t; and ε_j is the error term. *Year* is a dummy variable representing 2007 observations, *decrease in competition level* is the dummy defined above, and their interaction is the DID estimator of interest.

Table 3 presents our DID estimation results. Model 1 (2) refers to startups operating in industries with high (low) competition levels in 2002. For both models, the coefficient on *year* is insignificant and very low in its magnitude, indicating that there is no systematic difference in cooperation propensity between 2002 and 2007. The coefficient on *decrease in competition level* is also insignificant and very low indicating that, overall, there is no systematic difference in the *initial* propensity to cooperate between startups that experienced a decrease in competition levels between 2002–2007

Table 2. Competition Level and Cooperation Propensity—Coarsened Matched Sample (CEM) and Generalized Method of Moments (GMM) Regressions

Dependent variable—Cooperation propensity	(1) CEM Matched sample	(2) GMM	(3) CEM Matched sample	(4) GMM	(5) CEM Matched sample	(6) GMM
Competition level 2nd quartile	−0.120*	−0.130*	−0.123*	−0.134*	−0.118*	−0.129*
	(0.058)	(0.064)	(0.062)	(0.062)	(0.057)	(0.057)
Competition level 3rd quartile	−0.090*	−0.075*	−0.097*	−0.077*	−0.099*	−0.080*
	(0.045)	(0.031)	(0.048)	(0.034)	(0.043)	(0.037)
Competition level 4th quartile	0.047*	0.019*	0.045*	0.016*	0.040*	0.014*
	(0.022)	(0.009)	(0.021)	(0.008)	(0.020)	(0.006)
Weighted patent citations	−0.037*	−0.020*	−0.040*	−0.022*	−0.039*	−0.022*
	(0.017)	(0.009)	(0.018)	(0.010)	(0.018)	(0.023)
Weighted patent citations × Competition level 2nd quartile			−0.105*	−0.085*		
			(0.049)	(0.042)		
Weighted patent citations × Competition level 3rd quartile			0.090*	0.054*		
			(0.035)	(0.023)		
Weighted patent citations × Competition level 4th quartile			0.151*	0.091*		
			(0.0751)	(0.044)		
Innovativeness	−0.032*	−0.015*	−0.042*	−0.013*	−0.033*	−0.017*
	(0.014)	(0.007)	(0.019)	(0.006)	(0.015)	(0.008)
Innovativeness × Competition level 2nd quartile					−0.045*	−0.065*
					(0.019)	(0.028)
Innovativeness × Competition level 3rd quartile					0.080*	0.070*
					(0.036)	(0.033)
Innovativeness × Competition level 4th quartile					0.097*	0.101*
					(0.042)	(0.047)
Advertising intensity	−0.122	−0.160	−0.119	−0.165	−0.122	−0.172
	(0.081)	(0.091)	(0.079)	(0.094)	(0.098)	(0.095)
Capital intensity	−0.148*	−0.128*	−0.151*	−0.131*	−0.145*	−0.134*
	(0.065)	(0.057)	(0.069)	(0.065)	(0.062)	(0.062)
Ln_revenues	−0.117*	−0.039*	−0.120*	−0.043*	−0.124*	−0.039*
	(0.054)	(0.018)	(0.060)	(0.023)	(0.052)	(0.017)
No. of VCs	0.084*	0.120*	0.082*	0.122*	0.080*	0.119*
	(0.040)	(0.055)	(0.039)	(0.057)	(0.033)	(0.053)
Complementary assets	−0.091*	−0.119*	−0.088*	−0.121*	−0.103*	−0.118*
	(0.045)	(0.058)	(0.043)	(0.055)	(0.048)	(0.054)
Investments	0.024	0.031	0.027	0.030	0.026	0.028
	(0.035)	(0.019)	(0.032)	(0.017)	(0.018)	(0.019)
Product models	0.093	0.093	0.095	0.090	0.104	0.093
	(0.085)	(0.089)	(0.087)	(0.091)	(0.082)	(0.094)
Age	0.099	0.068	0.098	0.069	0.102	0.071
	(0.103)	(0.091)	(0.100)	(0.094)	(0.078)	(0.090)
Industry fixed effects	+	+	+	+	+	+
Year fixed effects	+	+	+	+	+	+
No. of firm-year observations	494	560	494	560	494	560
R squared	0.17		0.20		0.19	
Sargan Test (Prob > Chi^2)		0.377		0.389		0.361
2nd order serial correlation (Pr> *Z*)		0.424		0.435		0.412
Wald test		489.630		501.720		465.310

Notes. Robust standard errors in brackets. Constants not reported.
*Statistically significant at 5%.

and startups that did not. Our coefficient of interest is the coefficient on the DID estimator which is negative and significant; indicating that startups in markets with initially high competition levels that experienced a decrease in market competiveness are 18% less likely to cooperate than startups in markets with initially high competition levels that did not experience such a decrease. Model 1 further indicates that higher *weighted patent citations* for high market competition level startups further decreases *cooperation propensity* by 11%, while higher *innovativeness* decreases it by 8%. These results indicate a stronger decrease in cooperation propensity for high market competition level startups with a high degree of innovativeness.

In contrast, the coefficient on our DID estimator in model 2 is positive and significant, indicating that startups in markets with initially low competition levels that have experienced a further decrease in competition levels are 14% more likely to cooperate than startups in markets with initially low competition levels that have not experienced such a decrease. Model 2 further indicates that higher *weighted patent citations* increases the propensity of low competition level startups to cooperate by 7%, while higher *innovativeness* increases it by 9%. These results indicate that startups operating in low competition markets with more progressive innovations exhibit a higher increase in the propensity to cooperate with incumbents than less innovative startups. In terms of the control measures, the results of all models in Table 3 are consistent with those discussed in Table 2.

Table 3. Cooperation Propensity in Low and High Levels of Competition Given a Decrease in Competition Level

	(1)	(2)
Dependent variable—Cooperation propensity	High competition level	Low competition level
Year (>2002)	0.007 (0.081)	0.005 (0.076)
Decrease in competition level (treatment)	0.009 (0.127)	0.006 (0.120)
Year × *Decrease in competition level*	−0.178* (0.081)	0.143* (0.062)
Weighted patent citations	−0.108* (0.051)	0.068* (0.028)
Innovativeness	−0.082* (0.036)	0.089* (0.043)
Advertising intensity	−0.151 (0.080)	−0.125 (0.088)
Capital intensity	−0.132** (0.028)	−0.150* (0.074)
Ln_revenues	−0.129** (0.027)	−0.126** (0.035)
No. of VCs	0.068* (0.032)	0.085* (0.042)
Complementary assets	−0.090* (0.040)	−0.110* (0.055)
Investments	0.025 (0.019)	0.024 (0.018)
Product models	0.132 (0.080)	0.125 (0.084)
Age	0.098 (0.080)	0.105 (0.090)
Industry fixed effects	+	+
No. of firms	51	42
No. of firm-year observations	102	84
R squared	0.36	0.41

Notes. Robust standard errors in brackets. Constants not reported.
**Statistically significant at 1%; *statistically significant at 5%.

Robustness Analysis

We have conducted several additional analyses to test the robustness of our results (all are available from the authors upon request). Following Hsu (2006), we use the number of cooperation agreements (licensing and strategic alliances) with market incumbents as an alternative measure of startup-incumbent cooperation propensity. This measure is computed based on licensing and alliance announcements in secondary sources, such as Lexis Nexis Academic, and archives of leading financial newspapers in Israel. Since the number of alliances was heavily skewed to the left, we have performed a log transformation of this measure. The regression results for this alternative dependent variable are consistent with those reported in the Regression Analysis section.[20]

In addition, we have replaced our competition level measure with two alternative measures. The first measure is *concentration ratio*, referring to the U.S. market share of the four largest incumbents in each six-digit NAICS industry, as a measure for competition level, where greater concentration reflects lower competition markets. Given that such data is only reported every five years, as part of the economic census, we also assume that concentration measures are unlikely to change drastically within a two-year interval. As such, data referring to the years 2000–2004 are assigned the 2002 concentration measures, and data referring to 2005–2007 are assigned the 2007 concentration measures. The second measure we use is the Herfindahl-Hirschman Index (HHI) of incumbents' market shares in each six-digit NAICS industry. Our results remain fully robust to the use of both these alternative competition level measures. While neither of the measures we have used is a perfect measure of competition level, each of these measures captures different aspects of competition level; and thus the consistent results we get under both measures serve to corroborate our original findings.

To complement our CEM procedure, we have also used propensity scored matching as an alternative matching technique. We estimate a probit model of the decrease in competition level (between 2002 and 2007) using the same fitted covariates used for the CEM as estimates of the propensity score $P(\textit{decrease in competition level}_i = 1 \mid X_i)$. Comparison of the sample means of X_i for observations where there is a decrease in competition level and observations where there is no such decrease reveals that the percentage of differences are statistically significant for most of the fitted covariates (all but complementary assets), yet trimming the sample diminishes the difference. We therefore drop all observations that do not fall on the common support of the estimated propensity score distribution, and weigh the included observations by the inverse probability of being treated to create a balanced sample of 482 treated and control observations (Imbens 2004). We used this matched sample to re-run the models described in Table 2, and received similar results for those received in our CEM analysis.

Another relevant treatment that can be used to test our hypotheses is the possible effect of an *increase* in competition level. We have therefore defined another binary treatment measure, as follows:

$$\textit{Increase in competition level}_{jt} = \begin{cases} 1 & \dfrac{\textit{market value added}}{\textit{market revenues}}, \quad \textit{decreased by } 10\% \textit{ or more between } 2002 \textit{ and } 2007; \\ 0 & \textit{otherwise}. \end{cases}$$

This measure reflects whether startups have experienced an increase in competition level. Re-running the regression models in Table 3, we find that startups in markets with initially high competition levels that experienced a further increase in competition level exhibit a significantly higher propensity to cooperate, relative to startups in markets with initially high competition that did not experience a further substantial increase in competition level. In addition, we find that startups in markets with initially low competition level that experienced an increase in competition level exhibit a significantly lower propensity to cooperate relative to startups in markets with initially low competition that did not experience such an increase. These results are fully consistent with our mainline results. Furthermore, the results show that *weighted patent citations* and *innovativeness* negatively moderate *cooperation propensity* for high market competition startups, but positively enhance it for low market competition startups. This supports the view that higher quality technological innovation attenuates startup-incumbent cooperation propensity in high to moderately high competition level markets, but intensifies startup-incumbent cooperation propensity in moderately-low to low competition level markets.

In another set of robustness tests, we have substituted our *weighted patent citations* measure with the number of patents. Results for this alternative measure remained consistent with the results presented in Tables 1–3. We have further replaced our *innovativeness* measure with the ratio of a startup's annual R&D expenses to the average R&D expenses of all other sampled startups belonging to the same six-digit NAICS industry. In this case as well, we receive results that are consistent with our original results, albeit with a slight decrease in significance levels.

Discussion

Our analysis brings to the forefront the role of the level of competition as an important driver in startups and market incumbents' decision whether to cooperate on commercializing startups' innovations. Our empirical results show that the level of competition has a U-shaped relationship with the cooperation propensity of startups and market incumbents. Below we offer some rationale for why one might expect the likelihood of cooperation between startups and incumbents to be higher in markets with either high or low levels of competition as compared to markets with moderate competition levels. We also discuss the intuition behind the contingent effect of innovativeness.

Taxonomy: The Revenue Expansion, Revenue Sharing, and Imitation Effects

In general, three major factors interplay in the decision of startups and incumbents on their extent of cooperation when commercializing startups' technological innovations: (1) the degree of competitive advantage that incumbents may have over startups in terms of superior complementary assets, strong brand names, and loyal customers (Singh and Mitchell 2005, Rothaermel 2001); (2) the need to share revenues between startups and incumbents in return for using the incumbents' complementary assets, brand recognition, and reputation; and (3) the potential risk of imitation by market incumbents (Gans and Stern 2003, Hsu 2006, Teece 1986). We refer to these as *revenue expansion*, *revenue sharing*, and *imitation effects*, correspondingly.

The *revenue expansion effect* builds on RBV reasoning—suggesting that incumbents and startups possess complementary unique and hard-to-imitate capabilities (Barney 1991, Madhok 1997) that can be combined through cooperation. The *revenue sharing* and *imitation effects* build on TCE reasoning, specifically highlighting bargaining power and opportunistic imitation on the behalf of incumbents, leading to the risk of proprietary knowledge spillover threatening the sources of competitive advantage that high-tech startups obtain (Gans et al. 2002, Teece 1986, Williamson 1985).

Incumbents' advantage in the market typically allows them to enjoy higher prices, larger market shares, and lower costs. Thus, cooperation with incumbents in commercializing their technological innovations enables startups to charge higher prices, gain access to a larger share of the market, and get access to more effective marketing, distribution, and other complementary assets. These benefits, however, may come at a cost. Cooperating with incumbents requires sharing sales revenues with incumbents. In addition, the ability of startups to capture the value that their innovations create depends, among other things, on the probability that market incumbents would not imitate the newly-introduced innovations (Gans et al. 2002, Teece 1986). As discussed in the literature, under cooperation, imitation may result from unintended disclosure (Arora et al. 2001) in addition to reverse engineering, making imitation under cooperation more probable than imitation under competition (Gans et al. 2002, Khanna et al. 1998). This means that, for startups, the revenue expansion effect goes in an opposite direction to that of the imitation and revenue sharing effects.

For market incumbents, in contrast, the revenue expansion, imitation, and revenue sharing effects go in the same direction—increasing incumbents' expected value from cooperation.[21] Specifically, the additional value from the ability to sell the innovations of startups while using their own complementary assets more efficiently and reinforcing their brand recognition and reputation (Singh and Mitchell 2005) makes cooperation an attractive opportunity for incumbents. As suggested in TCE theory, market incumbents may choose to cooperate with startups to learn about the specifications of new technologies and, in turn, develop and sell the innovations on their own (Baum et al. 2000, Kale et al. 2000, Khanna et al. 1998, Rothaermel 2001). Potential imitation then further increases the incumbents' expected value from cooperation.

Importantly, our empirical findings suggest that the magnitude of the revenue expansion, imitation, and revenue sharing effects depends on competition level. Specifically, in markets with low competition levels, few established incumbents typically possess large market shares and strong market power, resulting in a large revenue expansion effect in such markets. The value of the revenue expansion effect decreases as the degree of competition in the market increases, as the incumbents' market share and market power decrease. The revenue expansion effect, thus, decreases with competition level.

The relationships between the level of competition and the imitation and revenue sharing effects are a bit more subtle. The magnitude of both effects is directly linked to the expected revenues for startups, should they choose to directly compete in the market. These expected revenues are small in both markets with high and low levels of competition due to the startups' difficulty in attracting customers and their inability to charge a large premium for their products. The source of this difficulty, however, differs in markets with high and low competition levels. In markets with low competition, it is hard for startups to enter the market, as market incumbents enjoy a large share of loyal customers, strong brands, and reputation (Nerkar and Shane 2003). Their dominant position allows incumbents to charge high price premiums while still enjoying large market shares—suggesting a large expected revenue expansion effect in case of cooperation. Furthermore, the incumbents' strong position in such markets makes it hard for startups that choose to directly compete in the market to grab market share. Taken together, this suggests that the attractiveness of cooperation in low competition markets is mostly driven by the large revenue expansion effect due to higher prices and larger potential market.

In contrast, markets with high competition levels are typically characterized by low margins and small market shares for all (Porter 1980, Schmalensee 1989). Consequently, the expected profitability for new entrants is very low, and as a result, the expected loss due to increased imitation is low. The revenue expansion effect in such markets is small as well, because the incumbents' market share is also limited. Nevertheless, the revenue expansion effect is likely to dominate the imitation and revenue sharing effects as cost advantages due to the incumbents' superior complementary assets are likely to be important drivers for capturing the value of startups' innovations in high competition markets. For example, in the extreme case of a market with perfect competition, only firms with cost advantages are able to enjoy positive economic value. That is, while the ability to enjoy access to the incumbent's customers at a marked-up price is definitely of value in markets with high competition, the advantage of cooperation in such markets is mostly cost-based. This, again, limits the ability of startups to independently build a large customer base, and subsequently implies low imitation and revenue sharing effects as the loss from the increased probability of imitation is very low—as is the loss from sharing low revenues with incumbents (relative to the case of competing with them).

It is, thus, in markets with moderate competition levels that the imitation and revenue sharing effects are at their maximum. In such markets, it is easier for startups to attract customers and penetrate the market. Furthermore, the market power of incumbents in such markets is modest. Consequently, the revenue expansion effect, as a result of the larger market share and markups, may not be large enough to compensate for the increased probability of imitation and the need to share profits with incumbents, lowering the propensity to cooperate.[22]

The Dual Effect of Startups' Innovativeness

The degree of startups' innovativeness determines two main aspects that crucially affect their incentives to cooperate: the potential markup on the new innovation and the strength of IPR protection the innovation provides. In particular, RBV reasoning as well as other perspectives imply that the more progressive an innovation, the larger the markup one can charge for it—increasing the value for both startups and incumbents (Barney 1991, Harhoff et al. 2003, Shaked and Sutton 1987). Moreover, TCE reasoning suggests that the more progressive an innovation, the stronger the IPR protection it provides, whether it is by granting the startups a stronger and broader patent protection or by making the innovation more complex and harder to be fully imitated even without patent protection (Cohen et al. 2000, Trajtenberg 1990, Lerner

1994, Reitzig and Puranam 2009). That is, an increase in innovativeness decreases the imitation effect for startups. Furthermore, TCE reasoning also suggests that the degree of innovativeness also crucially affects the revenue sharing effect. Specifically, the higher potential price for more innovative products, due to the greater willingness to pay for more progressive innovations, increases the value the innovation creates, and as a result, improves the startups' bargaining power when negotiating with incumbents (Gans et al. 2002, Trajtenberg 1990).

Our empirical results imply that the effect of innovativeness on the propensity to cooperate depends on the level of competition. The intuition behind this goes back to the magnitude of the revenue expansion, imitation, and revenue sharing effects. In general, greater innovativeness decreases the probability of imitation and thus makes the option of direct competition more attractive for the startup. While greater innovativeness also decreases the revenue sharing effect, in markets with high competition, the revenue expansion effect is typically very small. As a result, the effect of the decrease in the probability of imitation is likely to outweigh the decrease in the revenue sharing effect, thereby decreasing the propensity of startup-incumbent cooperation.

In contrast, in low competition markets, the incumbents' complementary assets, reputation, and brand recognition are stronger (Nerkar and Shane 2003, Schmalensee 1989) and substantially limit the potential for startups to gain market share and profits through competition. Under such conditions, greater innovativeness (implying lower imitation effect) may not suffice to allow startups to effectively compete in the market. In this case, the stronger IPR protection due to greater innovativeness can be more effectively used for decreasing the revenue sharing effect, as a result of the increase in the startup's bargaining power. This, in turn, increases the propensity of startups to engage in cooperation with incumbents. Taken together, while in high competition markets greater innovativeness has a stronger effect on reducing the imitation effect than on allowing greater revenue sharing, this relationship flips in low competition markets. Hence, startup-incumbent cooperation propensity, for more innovative startups, is likely to decrease in high competition markets, but increase in low competition markets.

Our taxonomy allows us to disentangle the different effects one should consider when choosing whether to compete or cooperate. Table 4 presents the interaction between the effects we identify on the propensity of startups and incumbents to cooperate. The table shows that for startups, the revenue expansion effect likely outweighs the sum of the imitation and revenue sharing effects in markets with either high or low competition, but not in markets with moderate competition. It is this nonmonotonic relationship between competition level and the imitation and revenue sharing effects for startups that drives our results and analysis. Table 4 further demonstrates how greater startups' innovativeness differently affects the magnitude of change in the revenue sharing and imitation effects, leading to decreased cooperation propensity in high competition markets, but to an increased cooperation propensity in low competition markets.

Our findings extend the traditional TCE-oriented view that startups and incumbents are likely to collaborate when they exchange relatively simple knowledge, but will prefer to compete when they need to exchange more complex knowledge, which is difficult to transact (Arora and Fosfuri 2003, Anderson and Gatignon 1986, Williamson 1985). To the extent that greater innovativeness infers greater knowledge complexity, our findings suggest that greater knowledge complexity will have opposing effects on cooperation propensity in low and high levels of competition.

Table 4. Taxonomy: Revenue Expansion, Imitation, and Revenue Sharing Effects and Cooperation Propensity

Level of competition	High	Moderate	Low	Intuition
Revenue expansion effect	Small	Medium	Large	Function of incumbents' market power
Revenue sharing and imitation effects	Insignificant	Large	Small	Function of startups' ability to grab market share
Prediction	Greater *cooperation* propensity	Greater *competition* propensity	Greater *cooperation* propensity	
		Effect of greater startups' innovativeness		
Revenue expansion effect	Remains small		Remains large	Function of incumbents' market power
Revenue sharing effect	Somewhat decreases		Significantly decreases	Function of startups' increased bargaining power
Imitation effect	Significantly decreases		Somewhat decreases	Due to ease of imitation
Prediction	*Decreases* cooperation propensity		*Increases* cooperation propensity	Depends on which effect dominates

The focus of this study on competition links it to related work on the incentives to license innovations and the competition level of the markets for technology (Fosfuri 2006, Arora and Fosfuri 2003, Arora and Gambardella 2010). Our study, however, makes an important deviation from this stream of literature. The focus of the aforementioned literature is on the decisions of large incumbents whether to keep the rights of their novel innovations solely to themselves or license these technologies to other competitors in the market. Licensing, in this case, would result in profit dissipation, due to enhanced competition and reduced margins. In contrast, our analysis focuses on startups' entry into new markets where, at least in the short term, they are not likely to significantly affect overall competition level. Specifically, if a startup competes with the incumbent, it is a small market player and thus does not affect competition level, and if the startup collaborates with an incumbent, its innovative products replace those of the incumbent.

Our setup studies startup firms entering a new *foreign* market. As such, to a large extent, the current study bears important implications for foreign market entry research and especially startups' foreign market entry (Hashai 2011, Zahra et al. 2000)—that is, foreign market entry decisions should consider the level of competition in the hosting market. Indeed, many of our arguments build on TCE and RBV reasoning that have played a significant role in this literature. Specifically, the revenue expansion effect builds on RBV reasoning, where we argue that startups possess technological advantages (often referred to as "ownership advantages" in this literature) while incumbents possess local market advantages that may be complementary (Agarwal and Ramaswami 1992, Delios and Beamish 1999). The imitation effect corresponds to TCE reasoning, highlighting the risk of proprietary knowledge spillover when penetrating foreign markets through collaboration (Agarwal and Ramaswami 1992, Anderson and Gatignon 1986, Brouthers 2002, Buckley and Casson 1998, Hennart 1988, Hill et al. 1990). The foreign market entry literature has acknowledged a central cost (or liability) faced by firms entering a foreign market; that is, the "liability of foreignness" (Hymer 1976, Zaheer 1995). This liability makes foreign startups even more inferior to host market incumbents, due to their geographic and cultural distance, lack of legitimacy, and lack of familiarity of the foreign market penetrated (Chan and Makino 2007, Fan and Phan 2007, Hashai 2011). The existence of such a liability for startups entering foreign markets suggests that our setting captures some kind of an upper bound of the competitive disadvantages of startups relative to incumbents. Domestic startups share many of the competitive disadvantages that foreign startups face relative to incumbents, and hence their cooperation propensity will likely follow the patterns identified in the current study. Yet, domestic startups do not bear the liability of foreignness, and hence may exhibit a somewhat greater propensity to compete against indigenous incumbents than Israeli startups, under similar levels of market competition.

Limitations and Future Research

Following our previous discussion, our findings should be further examined for domestic startups penetrating new markets in their home country. In particular, studies with a larger number of firm-year observations, capturing year-to-year changes in the level of market competition, are important to strengthen the external validity of our results. Moreover, in this study, we have focused on the U.S. market where IPR protection and enforcement are regarded as being high. Additional studies that focus on institutional environments with varying levels of IPR protection strength and enforcement are important to enhance the generality of our findings. In addition, we have focused on patent citations and startups' R&D investments as measures of the degree of startups' innovativeness and its strength of IPR protection. It is, therefore, important to test whether our findings hold under alternative innovativeness measures.

Obviously, many additional factors come into play when determining the propensity of startups and incumbents to cooperate on commercializing the innovations of startups. For example, the experience and personality traits of top management may become dominant determinants of market entry mode. Startup and incumbent managers with vast cooperation experience may exhibit a greater tendency toward cooperation, whereas managers with experience in direct competition may favor that strategy. While our analysis and results provide a baseline examination of the drivers of cooperation propensity, further research would be needed to specify these factors and to formulate and test a more comprehensive model of the drivers of cooperation propensity during startup's market entry, given the specific characteristics of top management.

In our analysis we assume that startups only consider cooperation with incumbents offering competing products. Startups, however, may choose to cooperate with incumbents offering complementary products. In fact, considering both substitute and complementary products may require a more elaborate framework where startups and incumbents simultaneously compete and cooperate (Brandenburger and Nalebuff 1996) in the same market. The considerations of both startups and incumbents on how to devise their cooperative and competitive strategies are likely to be different under such circumstances. In a similar vein, startups may combine both cooperation and competition when entering new markets as a result of different competition levels at submarkets within the host market (e.g., different geographic or different product markets in which startups operate). Such combination may also result from limited resources of startups leading them to compete in some submarkets, while being forced to cooperate with incumbents in others. It may also be the result of startups' desire to prevent complete dependence on incumbents as means to avoid hold-up problems (Williamson 1985). As such, more refined data on the level of competition in submarkets and of the specific distribution of competition versus cooperation with market incumbents in such submarkets may likely provide further insights on the choice of high-tech startups and incumbents on whether to compete, cooperate, or combine the two modes.

Finally, our taxonomy introduces three different effects: the revenue expansion, revenue sharing, and imitation effects. Unfortunately, we do not have the required fine-grained firm level and deal level data needed to measure these effects (e.g., the percentage that each side gets from shared sales, whether the technology was imitated, etc.). Future studies that will directly estimate the different effects and their interaction are therefore vital to estimate the different effects in our taxonomy.

Conclusion

As a whole, the current study implies that competition level is an important factor in determining the market entry mode of startups, and that the value that startups and incumbents may capture when they either compete or cooperate is a function of the combination of both external factors (i.e., competition level) and internal factors (such as innovativeness). We show that different combinations of product market competition level and the degree of startup innovativeness are likely to lead to different market entry modes. Taking such combinations into account is therefore of utmost importance for executives in startups and in incumbent firms aiming to evaluate and devise their strategies for competition and cooperation.

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Appendix

Table A.1. Descriptive Statistics and Pearson Correlations ($n = 560$)

Variable	Mean (Std. deviation)	Range	1	2	3	4	5	6	7	8	9	10	11
1. *Cooperation propensity*	0.59 (0.22)	0–1	1										
2. *Competition level*	0.57 (0.10)	0.32–0.75	−0.084	1									
3. *Weighted patent citations*	32.14 (70.17)	4–592	0.073	0.061	1								
4. *Innovativeness*	Dummy	0–1	−0.210	0.043	0.354	1							
5. *Advertising intensity*	0.001 (0.003)	0–0.014	0.018	0.312	0.031	0.226	1						
6. *Capital intensity*	0.41 (0.19)	0.12–0.92	0.010	0.445	0.023	0.041	−0.132	1					
7. *Revenues in the United States* ($US Millions)	19.15 (22.14)	0–76.14	−0.142	0.082	0.051	0.066	0.024	0.017	1				
8. *Complementary assets*	93.22 (65.13)	5–246	0.005	−0.330	0.041	0.092	0.310	0.363	0.255	1			
9. *No. of VCs*	4.25 (1.08)	0–7	−0.039	0.051	0.121	0.161	0.031	0.155	0.094	0.136	1		
10. *Investments* ($US Million)	22.34 (11.54)	0–63	0.027	−0.110	0.041	0.135	0.131	0.339	0.216	0.138	0.071	1	
11. *Product models*	6.36 (4.21)	1–14	0.011	0.023	0.020	0.241	0.048	0.102	0.263	0.087	0.024	0.037	1
12. *Age*	4.82 (5.03)	3–10	0.020	−0.131	−0.035	0.011	0.170	0.230	0.423	0.213	0.142	0.118	0.052

Notes. All correlations above 0.08 are significant at the 5% level and above. Moderate positive correlations (above 0.30) are observed between: *weighted patent citations* and *innovativeness*; *complementary assets* and *advertising intensity*; *competition level* and *advertising intensity*; *capital intensity* and *complementary intensity*; and *age* and *revenues*.

Table A.2. First Stage Logit Model of Decrease in Competition Level and Comparison of Sample Means Before and After CEM Matching

Dependent variable—Decrease in competition level		t-test on Δ *before* CEM matching	t-test on Δ *after* CEM matching
Weighted patent citations	0.108* (0.051)	1.95*	1.12
Innovativeness	0.082* (0.036)	Dummy	Dummy
Advertising intensity	0.121* (0.059)	1.92*	0.88
Capital intensity	0.182** (0.057)	3.43***	1.37
Ln_revenues	0.147* (0.065)	2.14*	1.61
No. of VCs	0.088* (0.042)	2.23*	1.43
Complementary assets	0.190* (0.087)	0.53	0.34
Investments	0.038* (0.019)	2.90***	1.57
Product models	0.109 (0.088)	1.67	1.25
Age	0.076 (0.082)	1.82	1.10
Industry	+	Dummy	Dummy
No. of firm-year observations	560	560	494
Pseudo R squared *F*-test on joint significance	0.21	7.21***	1.85

Notes. Robust standard errors (clustered around strata) in parentheses. Constants not reported.
***Statistically significant at 0.1%; **statistically significant at 1%; *statistically significant at 5%.

Endnotes

[1] The European Union is the second largest market, with 18% of sales of the sampled firms.

[2] As such, formal publications of the Israeli Central Bureau of Statistics concerning high-tech startups in Israel are based on data from this source.

[3] "Core industry" is defined as the industry contributing the vast majority of revenues. In general, 90% of the firms in our sample are active in one or two six-digit NAICS industries only, with one industry usually being more dominant than the other in terms of the firm's revenues.

[4] T-tests did not reveal evidence of interviewer-specific bias in the collected data.

[5] Fifty-five percent of the interviewees were at the CEO level, 20% were at the chairperson level, and 25% were at the senior-management level (mostly CTOs, CFOs, and VPs of business development). The average tenure of interviewees in their firms was four years and six months, which is only four months less than the average firm age in the sample.

[6] U.S. market incumbents are defined as firms that operate in the same industry as the startup and own R&D and manufacturing facilities, to distinguish them from distributors and VARs (value-added resellers).

[7] This measure is likely to be a better proxy for competition level than measures reflecting industry concentration or the use of the number of firms in the industry, because concentrated markets may still be markets with high competition levels (e.g., aircraft manufacturing market), while fragmented industries may be very profitable. Yet, as a robustness test, we use industry concentration and the Herfindahl-Hirschman Index (HHI) as alternative proxies for competition level and get similar results (see the Robustness Analysis section).

[8] This measure is constructed by subtracting the cost of materials, supplies, containers, fuel, purchased electricity, and contract work from the value of shipments (products manufactured plus receipts for services rendered). The result of this calculation is adjusted by the addition of value added by merchandising operations (i.e., the difference between the sales value and the cost of merchandise sold without further manufacture, processing, or assembly) plus the net change in finished goods and work-in-process between the beginning- and end-of-year inventories.

[9] Ideally, we would have preferred to compare the R&D expenses of startups to industry level R&D expenses, but unfortunately, such data is not available at the six-digit NAICS level.

[10] This measure displays a high level of skewness and is therefore log-transformed.

[11] Likewise, VC backing may reflect the ex-ante preferences of startups to cooperate rather than compete, due to the transaction cost reduction implied by such backing (Gans et al. 2002, Hsu 2006).

[12] Given that *weighted patent citations* and *innovativeness* both capture the quality of technological innovation and are highly correlated, models including the interactions of the competition level quartiles with both measures exhibited high multicollinearity.

[13] We have repeated the same procedure, this time defining competition level quartile 4 as the reference quartile. Results (available upon request) show a decrease of about 8.5%–12.5% in cooperation propensity for quartile 1 observations, and remain consistent for quartiles 2 and 3. This regression formulation indicates that, in high competition level markets, greater innovativeness of startups (as in our two innovativeness measures) reduces cooperation propensity.

[14] Our results are unchanged if we allow the statistical software Stata to choose the values on which to coarsen the independent variables in the first-stage regression.

[15] Yet, the results are robust to forcing the matches to be one-to-one.

[16] See review in Bascle (2008).

[17] For the same reason, using Heckman (1979) correction is less appropriate in this case.

[18] The two right hand columns in Appendix Table 1 further show that before the matching procedure, most of the key covariates of startups that did not face a decrease in competition level are statistically different from those that did, and the joint significance of the differences is large ($F = 7.21$). Yet, the differences in the means once a control group is identified using CEM has become insignificant for all covariates. In addition, the first stage has ensured that control observations are matched for treated ones on the *innovativeness* dummy covariate as well as in six of the eight four-digit NAICS industries we have.

[19] Similar results are obtained when median rather than average is used.

[20] We further use either licensing or alliance agreements as our measure of cooperation propensity. In both cases, results remain consistent with our original results, suggesting that our results are not driven by the type of cooperation (licensing vs. alliance).

[21] It is noteworthy that incumbents may also face costs when cooperating with startups. Specifically, commercializing startups' innovations through licensing and/or strategic alliances may result in the cannibalization of sales of the incumbents' existing products.

[22] We summarize this in the top panel of Table 4.

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