The Effects of Downstream Competition on Upstream Innovation and Licensing

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Abstract

We consider an upstream innovator and two downstream competitors; and examine the impact of product market competition on the innovator’s R&D strategy, when she can license her innovations to either one downstream competitor (targeted licensing) or both (market-wide licensing). We show that downstream competition unambiguously increases the appeal of targeted licensing over market-wide licensing. Moreover, competition increases the innovator’s incentives to innovate under targeted licensing, but decreases these incentives under market-wide licensing. Thus, a threshold level of competition may exist such that above (below) that threshold, targeted (market-wide) licensing is optimal and innovation is increasing (decreasing) in competition. Using U.S. data across all industries over the period 1976 — 2006, we find empirical evidence that downstream competition has an U-shaped impact on upstream innovation. Data on licensing deals provides further empirical support that upstream innovators’ licensing strategy is the underlying economic mechanism. In particular, as downstream competition intensifies, targeted licensing strategy becomes more appealing to upstream innovators than market-wide licensing.

JEL Codes: L22, L24, O31, O32.

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1 Introduction

How does product market competition affect firms’ innovation strategies? This question has generated a lot of interest among academics over the past 50 years; and a common belief among economists in particular has been that competition increases rival firms’ incentives to innovate. As the empirical literature suggests, however, the impact of competition on innovation is not from clear-cut, and indeed may not be positive or even monotonic. The empirical evidence also suggests that instead of being instigated by the product market rivals themselves (as implicitly assumed in much of the theoretical literature); innovation in fact often takes place upstream from these competitors and is subsequently licensed to the downstream firms in technology markets. In this paper, we examine the impact of downstream competition on an upstream innovator’s optimal licensing and innovation strategies; and highlight a subtle theoretical connection between competition and innovation that may explain the tenuous relationship emerging from the empirical literature.

We consider a market for technology composed of an upstream innovator, and two firms competing in a downstream product market. These two downstream firms are located at each end of a Hotelling (1929) line, and we use the inverse of the “transport cost,” \( \theta = 1/t \) as our exogenous measure of competition. The innovator makes an investment in a cost-reducing innovation which, once generated, she can license either to one of the downstream competitors - “targeted” licensing - or to both - “market-wide” licensing. Importantly, targeted licensing allows one downstream firm to gain a cost advantage, and in turn a demand advantage over its rival; and thus to enjoy strong demand and a large markup. In contrast, market-wide licensing allows each downstream firm to avoid facing both cost and demand disadvantages relative to its rival, a situation associated with weak demand and a small markup. We exploit this difference between licensing strategies to derive and explain two key insights.

First, competition increases the innovator’s licensing revenue from targeted licensing, but reduces her revenue from market-wide licensing, thereby unambiguously increasing the relative appeal of targeted licensing to the innovator. To explain this, we show that competition has two offsetting effects on licensing revenue. On the one hand, it leads downstream firms to lower their prices and hence reduces their price-cost margins. This rent reduction effect reduces downstream firms’ willingness to pay for the license, and in turn the innovator’s licensing revenue, under both licensing strategies. On

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1 For simplicity, throughout the paper we generally use “competition” to refer to “product market competition”.
2 See, e.g., the recent theoretical work of Raith (2003), and Baggs and Bettignies (2007).
3 We discuss the empirical literature in later Section 1.
the other hand, competition enables a firm with a small innovation-driven cost advantage to “steal” more business from its rival and to increase demand at their expense. Under targeted licensing, this business stealing effect increases the unique licensee’s payoff if the licensed is purchased, and hence increase that firm’s willingness to pay for the license and the innovator’s licensing revenue. Under market-wide licensing, business stealing increases both firms’ willingness to pay by decreasing the pay-off that they would obtain if they did not purchase the license while the other firm did. Thus business stealing increases licensing revenue under both licensing strategies.

The distinct effects of competition on licensing revenue across licensing strategies comes from the differential strength of the business stealing effect. Under targeted licensing, business stealing effect is strong. Competition increases the demand advantage of the licensed firm, and this increase in demand has large effect on that firm’s payoff because as mentioned above that firm - having gained a cost advantage over its rival - enjoys a large markup. In this case business stealing dominates rent reduction, and the net impact of competition on the licensing candidate’s willingness to pay for the license is positive. In contrast, under market-wide business stealing is weak. Competition exacerbates the demand disadvantage each firm would have if it did not purchase the license while its rival did, but the impact of this decrease in demand on the firm’s payoff is small because the firm with a cost disadvantage relative to its rival would enjoy a small markup. Thus in that case business stealing is dominated by rent reduction, and the net impact of competition on the licensing candidate’s willingness to pay for the license is negative.

The second key insight of the model concerns the impact of downstream competition on the upstream innovator’s incentives to innovate, which is shown to differ across licensing strategies. Competition affects the innovator’s marginal benefit from innovation through business stealing and rent reduction effects similar to the ones described above. Larger demands and markups under targeted licensing generate a strong business stealing effect, strong enough to offset rent reduction and to yield a positive effect of competition on innovation. In contrast, lower demands and markups under market-wide licensing generate a weak business stealing effect and a negative impact of competition on innovation.

Taken together, these insights suggest that the relationship between competition and upstream innovation is inextricably connected to the innovator’s licensing strategy. Indeed, we show that a threshold level of downstream competition may exist such that below this threshold market-wide licensing is optimal and innovation decreases with competition; while above the threshold targeted
licensing is optimal and innovation increases with competition.

To test the predictions based on our theoretical model empirically, we use a large sample of publicly traded U.S. firms over the years 1976 – 2006. Using patent as a metric for innovation and Lerner index for competition, we find strong empirical evidence that there is an

shaped relationship between downstream competition and upstream innovation. Moreover, the U-shaped relationship between downstream competition and upstream innovation becomes more pronounced for larger firms than for smaller ones, and for firms in less innovative industries. Next, in order to mitigate endogeneity concerns, we use the reductions in import tariff rates as a quasi-natural experiment; for the reason that firms in industries with large reductions in import tariff rates face a high level of industry competition. Overall our identification tests suggest that downstream competition has an U-shaped causal impact on upstream innovation. Further to our understanding of the U-shaped relationship is to explore the underlying economic mechanism. Consistent with the implications from our theoretical model, data on licensing deals provides strong support that upstream innovators’ licensing strategy is the channel through which downstream competition has an impact on upstream innovation. Specifically, our empirical evidence suggests that downstream competition increases the appeal of targeted licensing relative to market-wide licensing; and upstream innovation increases (decreases) in downstream competition under targeted (market-wide) licensing.

Our model is related to the theoretical literature on competition and innovation, which goes back to Stigler’s (1958) “survivor principle”: competition promotes innovation by weeding out less innovative, and hence less efficient, firms in the industry. More recently, the literature has focused on the connection between competition, agency costs, and innovation; suggesting that competition may spur/hinder innovation by mitigating/exacerbating agency problems (Hart, 1983; Scharfstein, 1988; Hermelin, 1992; Schmidt, 1997; Raith, 2003; Baggs and Bettignies, 2007). And as detailed in Vives’s (2008) comprehensive analysis of the competition-innovation connection under various demand specifications, even absent agency costs, competition may - by affecting firms’ marginal product of innovation - have an impact on equilibrium innovation. In this literature, though, all innovation investments are made by competing firms, and upstream innovation is not considered.

Our model is also related to the literature on “outsider patentee” licensing, i.e. the strand of the licensing literature which assumes that the innovation is undertaken by an upstream innovator who then licenses the innovation to firms competing in the downstream product market. This line of

\[\text{See also Cabral and Riordan (1989) for an analysis of incentives for cost reduction under price-cap regulation.}\]
research examines various aspects of licensing - e.g. number of licenses to be sold, welfare implications, timing of licensing - under different licensing environments, including fixed fees or royalties (Kamien and Tauman, 1986), auctions (Katz and Shapiro, 1986; Muto, 1993; Schmitz, 2002; Poddar and Sinha, 2004), two-part tariffs (Kamien and Tauman, 1984; Farrell and Shapiro, 2008; Fauli-Oller and Sandonis, 2002, 2012), and bargaining (Allain, Henry, and Kyle, 2009). However it generally treats innovation as exogenous rather than as an endogenously determined variable; and fails to consider the impact of competition on innovation and licensing strategies;\(^5\) two key limitations given our purpose here.\(^6\)

Two noteworthy exceptions include Arrow's (1962) classic paper on competition and innovation, which suggests that innovation incentives should be greater for an upstream innovator selling to firms in a competitive downstream market than for a monopolist in that downstream market; and the more recent work of Fauli-Oller \emph{et al.} (2011), which shows that mergers in a downstream market (and the concomitant reduction in competition) should be associated with increased R&D investments by the upstream innovator supplying the downstream competitors.\(^7\) Importantly, in both Arrow (1962) and Fauli-Oller \emph{et al.} (2011) the upstream innovator supplies all of the downstream competitors. In contrast, we show that the innovator’s licensing decision is itself endogenous and a function of competition in the industry, and may directly affect the innovator’s R&D strategy.

The other key strand of the licensing literature - on “insider patentee” licensing (e.g. Gallini, 1984; Gallini and Winter, 1985; Katz and Shapiro, 1987; Fauli-Oller and Sandonis, 2002; Arora and Fosfuri, 2003; Erkal, 2005) - examines the voluntary transfer of technology/innovation from one downstream competitor to another. Within this line of research, Gallini and Winter (1985) - in comparing endogenous innovation levels by downstream competitors when licensing is and is not allowed - is perhaps closest to our paper. But their model does not consider outsider patentee licensing, nor does it examine the impact of competition on licensing or innovation.

Also closely related to this paper are the works of Arora and Fosfuri (2003) and Bagchi (2008),\(^5\) Allain \emph{et al.} (2011) do examine the impact of market structure in a licensing model, but their focus is on the timing of licensing rather than on the innovation itself, which remains exogenous to the model.\(^6\) The recent work of Chatain (2014) examines the “the interplay between product market, strategic factor market, and resource development” in a framework that could be interpreted as one of outsider patentee licensing; and in that sense addresses a research question similar to ours. Our approach departs from his in two critical ways. First, we use a location model of competition (in contrast to his reduced-form approach to modeling competition) to place strategic interaction in the downstream product market at the forefront of the analysis. Second, we endogenize not only innovation decisions but also the licensing decisions, thus allowing us to unpack the specific, simultaneous and related effects of competition on both licensing and innovation strategies.

A related line of research examines the effects of downstream buyer power - rather than downstream product market competition - on upstream investment incentives. See for example Chen (2004), Battigalli \emph{et al.} (2007), Inderst and Shaffer (2007), and Inderst and Wey (2003, 2007, 2011).
which examine the impact of competition - measured as the degree of product homogeneity - on innovators’ licensing decision. In particular, when the innovator is a downstream competitor (Arora and Fosfuri, 2003), competition is shown to lead to more licensing, whereas when in the case of an outsider patentee (Bagchi, 2008) it leads to less licensing. Importantly, a firm’s innovation is exogenous in these models, thus precluding any analysis of the central question addressed here, namely the impact of competition on innovation when licensing plays an important role.

Our theoretical model contributes to both competition-innovation and licensing literatures, indeed providing a valuable link between them. On the one hand, it examines the competition-innovation relationship in a new light, through upstream licensing. On the other hand, it extends the licensing literature by placing competitive interaction and its effects at the centre of the analysis, and by endogenizing both licensing and innovation strategies.

The empirical literature on the impact of competition on innovation appears to be somewhat ambiguous. Competition is shown to have a positive (Geroski, 1990; Bertschek, 1995; Blundell et al., 1999), negative (Hashmi, 2013), or inverted-U (Aghion et al., 2005) effect on innovation. Similarly, in the trade literature the evidence points to both a positive (Teshima, 2010; Bloom et al., 2016) and a negative (Sherer and Huh, 1992; Gorodnichenko et al., 2010) relationship between competitive pressure from imports and innovation, and hence again fails to provide clear, unambiguous results.

While the focus of the literature on competition and innovation has been on innovation by competitors in the product market, in fact innovation is often performed upstream from these competitors, with the innovation being licensed to the downstream rivals in a vertical technology market (Arora et al., 2001, p.6). Much less work has been done, however, to analyze empirically the impact of downstream competition on upstream innovation⁹, and the underlying economic mechanism. Our paper contributes to the empirical literature by providing evidence of an U-shaped relationship between downstream competition and upstream innovation, and by exploring the channel of upstream licensing strategy through which downstream competition has an U-shaped impact on upstream innovation.

The paper is organized as follows. In Section 2, we set up the basic model and derive equilibrium outcomes under market-wide and targeted licensing. Section 3 analyzes the effects of competition on the innovator’s optimal licensing and innovation strategies. In Section 4, we introduce our model’s empirical implementation and results, check for robustness, address endogeneity concerns, and explore

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⁸See also the related work of Bagchi (2014). As well, Siebert and von Graevenitz (2010), which examines the impact of product market competition on the choice between ex ante and ex post licensing.

⁹See, e.g., the work of Sanyal and Ghosh (2013). They focus on U.S. electricity industry and find that downstream competition negatively affects upstream innovation.
the underlying economic mechanism. Finally, we conclude in Section 5. The extensions to our main model, the proofs of Lemmas 1 and 2, and of Proposition 2 are in the appendix; all other proofs follow directly from the text.

2 Basic Model

2.1 Setup

The setup of the model can be described as follows:

Firms and Consumer. Two firms, 1 and 2, are positioned at each end of a Hotelling (1929) line, with locations \( x_1 = 0 \) and \( x_2 = 1 \), respectively. The two firms face marginal costs \( c_1 = c_2 = c \), and compete in price \( p \).

Without loss of generality we posit that a unique consumer, whose location is random and uniformly distributed along the line, purchases one unit of the product from either Firm 1 or Firm 2. Firms 1 and 2 know the distribution of the location of the consumer, but they do not know the actual location on the line. At location \( x \), the consumer incurs a transport cost \( tx \) for travelling to Firm 1 and a cost \( t (1 - x) \) to visit Firm 2. The consumer enjoys conditional indirect utility \( U_1 = s - p_1 - tx \) from product 1 and \( U_2 = s - p_2 - t (1 - x) \) from product 2 (where \( s \) represents income), and selects the utility maximizing product. The resulting expected demand for Firm \( i \), \( i = 1, 2 \), is:

\[
d_i(p_i, p_j, t) = \frac{1}{2} + \frac{(p_j - p_i)}{2t}. \tag{1}
\]

Product Market Competition. The “Hotelling” parameterization of competition is a natural choice here, for two main reasons.\(^{10}\) First, given our ultimate purpose - comparative statics on the degree of competition - the transport cost \( t \), which measures the degree of horizontal product differentiation, or rather its inverse \( \theta = 1/t \), is an ideal parameter to represent what Sutton (1992, p.9) defined in his classic work as toughness of competition. Second, the Hotelling model is the simplest and most tractable framework to deal with, relative to other candidate modeling choices, and indeed offers general insights at the lowest analytical cost. Thus, as is common in the industrial organization literature, throughout the paper we use the degree of substitutability between products, \( \theta \), as our measure of competition. We restrict our attention to value of \( \theta \in \Theta \) with \( \Theta \equiv (0, 9/2) \), which ensures

\(^{10}\)See discussion of other models of competition in Section 4.
strict concavity of all maximization programs as well as positive equilibrium prices, demands and profits (see proofs of Lemmas 1 and 2).\textsuperscript{11}

**Innovation.** Upstream from the two product market competitors, an innovator is working on a cost-reducing innovation that can be licensed to the downstream firms. The innovator has two alternatives. Under *targeted licensing*, she chooses innovation level $\Delta_T$ and licenses it to Firm 1 only. We assume the innovator can commit to license to only one firm under targeted licensing; for example by making the innovation specific to that one firm, or contractually granting exclusive use of the innovation to that one firm.\textsuperscript{12} Under *market-wide licensing*, she chooses innovation level $\Delta_M$ and licenses it to both firms 1 and 2. An innovation $\Delta$ benefits the licensees by reducing the their marginal cost of production by $\Delta$; and costs the innovator $K_T(\Delta) = \Delta^2/2$ under targeted licensing and $K_M(\Delta) = \Delta^2/2 + h$, with $h \in \mathbb{R}_{++}$, under market-wide licensing. Parameter $h$ captures all additional transaction costs associated with negotiating the second license under market-wide licensing.

**Contracts.** We assume that downstream rivals’ profits and output cannot be verified by third parties such as courts, and are thus not contractible. This could arise for example if downstream managers can spend cash flows on “perks” which “may be difficult to distinguish from appropriate business decisions [...]” (Bolton and Scharfstein, 1996). This contractual incompleteness rules out two-part tariffs (fixed fee plus royalty) - which are based on profits or output measures - as possible licensing frameworks. We also assume that transaction costs associated with setting up auctions are prohibitively high, making auctions difficult to implement. Accordingly throughout the main text we focus on fixed fees as the licensing contracts between the innovator and downstream firms. This is not an unrealistic assumption. In the chemical industry for instance, contracts usually include fixed fees. While some innovators may set royalties on output, determined by industry norms at around 2%, others, like SEFs for instance, “tend to favor lump sum payments, unwilling or unable to track how the project does after commissioning” (Arora and Fosfuri, 2000). In Appendix B we also consider licensing contracts based on auctions, and on two-part tariffs; and show that the main results of our model continue to hold.

Thus, we assume that under market-wide licensing innovation $\Delta_M$ is licensed to firms 1 and 2.

\textsuperscript{11}In setting this type of simplifying parametric restriction we follow Raith (2003) and others.

\textsuperscript{12}Commitment is important here. As is well-known from the foreclosure literature, the innovator may have an incentive to sell a license to the second downstream firm after having sold a license to the first one. Anticipating this, the first licensee would have a lower willingness to pay for the license in the first place. See e.g. Rey and Tirole’s (2007) excellent review of the foreclosure literature.
respectively, for license fees $z_{1M}$ and $z_{2M}$; and that under targeted licensing, innovation $\Delta_T$ is licensed to Firm 1 for license fee $z_{1T}$.

**Timing of the Game.** At date 0, the innovator chooses between market-wide licensing and targeted licensing. At date 1, under market-wide licensing, the innovator selects $\{\Delta_M, z_{M1}, z_{M2}\}$; and under targeted licensing she selects $\{\Delta_T, z_{1T}\}$. At date 2, firms offered a license decide whether or not to purchase it, taking the license fee as given. Marginal costs of production are determined. At date 3, after observing each other’s marginal costs, firms 1 and 2 compete in price. Demands and profits are realized.

### 2.2 Market-Wide Licensing

Suppose the innovator plans to license innovations to both downstream firms. We derive the equilibrium by backward induction.

At date 3, price competition takes place between firms 1 and 2. Specifically, Firm $i$, $i = 1, 2$, chooses $p_i$ to maximize its expected payoff, taking costs and innovations as given:

$$\max_{p_i} \pi_i(\Delta_i, p_i, p_j, \theta) = \max_{p_i} (p_i - c + \Delta_M) d_i(p_i, p_j, \theta),$$

with expected demand $d_i(p_i, p_j, \theta)$ defined as in (1). Taking the first-order conditions (FOCs) with respect to price for $i = 1, 2$ and solving the resulting system of two equations yields the following equilibrium price-cost margin $P_i$:

$$P_i = p_i - c + \Delta_i = \frac{1}{\theta} + \frac{\Delta_i - \Delta_j}{3}. \quad (3)$$

Substituting equilibrium prices back into the expected demand, we obtain an expression for expected profits as a function of innovations:

$$\pi_i(\Delta_i, \Delta_j, \theta) = P_i(\Delta_i, \Delta_j, \theta) d_i(\Delta_i, \Delta_j, \theta) = \left[\frac{1}{\theta} + \frac{\Delta_i - \Delta_j}{3}\right] \left[\frac{1}{2} + \frac{(\Delta_i - \Delta_j)\theta}{6}\right], \quad (4)$$

where $d_i = \left[\frac{1}{2} + \frac{(\Delta_i - \Delta_j)\theta}{6}\right]$ is the expected demand for Firm $i$. Under market-wide licensing, of course, $\Delta_i = \Delta_j = \Delta_M$, and Firm $i$’s expected profits simplify to $\pi_i(\Delta_iM, \Delta_jM, \theta) = 1/(2\theta)$.

At date 2, as can readily be shown, in equilibrium Firm $i$ licenses innovation $\Delta_M$ from the innovator if and only if (iff) the payoff it can obtain if it buys the license is at least as large as its payoff if it
does not buy the license: \( \pi_i(\Delta_i, \Delta_j, \theta) - z_{iM}(\Delta_i, \Delta_j, \theta) \geq \pi_i(0, \Delta_j, \theta) \), with \( \Delta_i = \Delta_j = \Delta_M \).

At date 1, the foresighted innovator sets the highest license fee \( z_{iM} \) that she can extract from Firm \( i \), subject to both firms buying the license, which is simply:

\[
z_{iM}(\Delta_M, \theta) = \pi_i(\Delta_M, \Delta_M, \theta) - \pi_i(0, \Delta_M, \theta) = \frac{1}{2\theta} - \left[ \frac{1}{\theta} - \frac{\Delta_M}{3} \right] \left[ \frac{1}{2} - \frac{\Delta_M\theta}{6} \right].
\]

Under market-wide licensing, Firm \( i \) takes as given that Firm \( j \) has access to innovation \( \Delta_M \). The optimal license fee to charge Firm \( i \) - which is Firm \( i \)'s willingness to pay for the license - is the difference between Firm \( i \)'s profits if it obtains access to innovation \( \Delta_M \) - “symmetric profits” \( \pi_i(\Delta_M, \Delta_M, \theta) \), since in this case both rivals have access to the same innovation - and its profits without access to the innovation - “laggard profits” \( \pi_i(0, \Delta_M, \theta) \), since in that case Firm \( i \) has no access to the innovation while Firm \( j \) does.\(^{13}\) The innovator chooses innovation \( \Delta_M^* \) to maximize the following payoff:

\[
Z_M = z_{1M}(\Delta_M, \theta) + z_{2M}(\Delta_M, \theta) - K_M(\Delta_M).
\]

Using expression (31), and taking the FOC with respect to \( \Delta_M \), yields \( \Delta_M^* \) such that:

\[
-\frac{\partial\pi_1}{\partial \Delta_2}(0, \Delta_M^*, \theta) - \frac{\partial\pi_2}{\partial \Delta_1}(0, \Delta_M^*, \theta) = \frac{\partial K}{\partial \Delta_M}(\Delta_M^*).
\]

Clearly, a marginal increase in innovation \( \Delta_M \) has no impact on symmetric profits: \( \frac{\partial\pi_1}{\partial \Delta_M}(\Delta_M, \Delta_M, \theta) = \frac{\partial K}{\partial \Delta_M}(\Delta_M) = 0 \). This is because an increase in \( \Delta_M \) identically lowers the marginal costs of both firms, and these identical changes in marginal costs neutralize each other in the profit function.

In contrast, a marginal increase in innovation \( \Delta_M \) does reduce laggard profits for firms 1 and 2. An increase in \( \Delta_M \) reduces the profits that Firm 1 (resp. 2) makes if it does not license the innovation, because it increases the cost disadvantage Firm 1 would have relative to a licensed Firm 2 (resp. 1) in that case. By decreasing Firm 1’s and Firm 2’s laggard profits, an increase in \( \Delta_M \) raises these firms’ willingness to pay to license the innovation in order to avoid this laggard situation. These marginal effects on the firms’ willingness to pay and hence on the innovator’s licensing revenue are depicted on

\(^{13}\)This is a so-called “offer game,” in which the principal (innovator) makes simultaneous offers to the agents (downstream firms), examined by Segal (1999, 2003), Genicot and Ray (2006), and more recently Galasso (2008), among others. Equation (31) defines the cheapest way for the principal to ensure “acceptance” by agents, i.e. to have (accept, accept) as a Nash equilibrium. In principle, even if (31) holds, (reject, reject) may also be an equilibrium. Segal (1999) simply rules this equilibrium out by assuming that the principal can coordinate agents on his preferred equilibrium. We do not need this assumption here, as one can readily verify that - in our Hotelling framework, at the equilibrium innovation level \( \Delta_M = \frac{6}{5\pi_2/2} \) - we have \( \pi_i(\Delta_M, 0, \theta) - [\pi_i(\Delta_M, \Delta_M, \theta) - \pi_i(0, \Delta_M, \theta)] > \pi_i(0, 0, \theta) \), for \( i = 1, 2 \), ruling out (reject, reject) as an equilibrium.
the left-hand side of (27). The right-hand side represents the innovator’s marginal cost of innovating. As shown in Appendix A, solving the FOC for $\Delta^*_M$ yields a unique equilibrium:

**Lemma 1** Under market-wide licensing, a unique equilibrium exists, in which the innovator chooses innovation levels $\Delta^*_M = \frac{6}{\theta + 2\theta^2}$. This in turn implies downstream price-cost margins $P_1(\Delta^*_M, \Delta^*_M, \theta) = P_2(\Delta^*_M, \Delta^*_M, \theta) = 1/\theta$; and expected demands $d_1(\Delta^*_M, \Delta^*_M, \theta) = d_2(\Delta^*_M, \Delta^*_M, \theta) = 1/2$. License fees, and payoff to the innovator, simplify to $z_{1M} = z_{2M} = \frac{2(\theta + \theta^2)}{(9 + 2\theta^2)},$ and $Z^*_M = \frac{2}{(9 + 2\theta^2)} - h$, respectively.

### 2.3 Targeted Licensing

Suppose now that the innovator plans to license her innovation to Firm 1 only. Then:

At date 3, given that the innovator has licensed innovation $\Delta_T$ to Firm 1 but not to Firm 2, price competition is the same as in Section 2.2, and profits for firms 1 and 2 can be expressed using (24) as $\pi_1(\Delta_T, 0, \theta)$ and $\pi_2(0, \Delta_T, \theta)$, respectively.

At date 2, in equilibrium Firm 1 licenses innovation $\Delta_T$ from the innovator iff the payoff it can obtain if it buys the license is at least as large as its payoff if it does not buy the license: $\pi_1(\Delta_T, 0, \theta) - z_{12}(\Delta_T, 0, \theta) \geq \pi_1(0, 0, \theta)$.

At date 1, the foresighted innovator sets the highest license fee $z_T$ that she can extract from Firm 1, which is simply:

$$z_{1T}(\Delta_T, \theta) = \pi_1(\Delta_T, 0, \theta) - \pi_1(0, 0, \theta) = \left[\frac{1}{\theta} + \frac{\Delta_T}{3}\right] \left[\frac{1}{2} + \frac{\Delta_T \theta}{6}\right] - \frac{1}{2\theta}.$$  \((8)\)

Under targeted licensing, Firm 1 takes as given that Firm 2 does not have access to innovation $\Delta_T$. The optimal license fee to charge Firm 1 - Firm 1’s willingness to pay for the license - is the difference between its profits if it obtains access to innovation $\Delta_T$ - “leader profits” $\pi_i(\Delta_T, 0, \theta)$, since in this case Firm 1 has access to the innovation while Firm 2 does not - and its profits without access to the innovation - “symmetric profits” $\pi_i(0, 0, \theta)$, since in that case neither firm has access to the innovation.\(^{14}\)

The innovator chooses innovation $\Delta_T^*$ to maximize the following payoff:

$$Z_T = z_{1T}(\Delta_T, \theta) - K_T(\Delta_T).$$  \((9)\)

\(^{14}\)Alternatively, we could assume that in the event Firm 1 does not gain access to the innovation, Firm 2 would do so. This alternative setup is examined in the Auction Scenario in Appendix B, where similar results are shown to arise.
Using expression (8), and taking the FOC with respect to $\Delta_T$, yields $\Delta_T^*$ such that:

$$
\frac{\partial \pi_1}{\partial \Delta_1} (\Delta_T^*, 0, \theta) = \frac{\partial K_T}{\partial \Delta_T} (\Delta_T^*).
$$

(10)

Under targeted licensing, the innovator’s marginal benefit from innovation $\Delta_T$ works by increasing Firm 1’s innovation advantage if it does obtain access to the innovation, thus increasing Firm 1’s leader profits. This in turn increases Firm 1’s willingness to pay for the innovation, and the innovator’s equilibrium licensing revenue. As shown in Appendix A, solving the FOCs for $\Delta_T^*$, one obtains a unique equilibrium:

**Lemma 2** Under targeted licensing, a unique equilibrium exists, in which the innovator chooses innovation level $\Delta_T^* = \frac{3}{2 \theta}$. This in turn implies downstream price-cost margins $P_1 (\Delta_T^*, 0, \theta) = \left[ \frac{1}{\theta} + \frac{\Delta_T^*}{3} \right]$ and $P_2 (0, \Delta_T^*, \theta) = \left[ \frac{1}{\theta} - \frac{\Delta_T^*}{3} \right]$; and expected demands $d_1 (\Delta_T^*, 0, \theta) = \left[ \frac{1}{2} + \frac{\theta \Delta_T^*}{6} \right]$ and $d_2 (0, \Delta_T^*, \theta) = \left[ \frac{1}{2} - \frac{\theta \Delta_T^*}{6} \right]$. License fees, and payoff to the innovator, simplify to $z_{1T}^* = \frac{18 - \theta}{2(9 - \theta)^2}$, and $Z_T^* = \frac{1}{18 - 2\theta}$, respectively.

Note that here intra-industry differential firm performance emerges endogenously, similar to Zott (2003): expected profits are greater for Firm 1 than for Firm 2. While in Zott’s work this differential arises from differences in the timing, cost, and learning of resource development, here we emphasize the market for technology and the upstream innovator’s licensing strategy generating this differential.

3 Competition, Licensing and Innovation

The foregoing analysis suggests a key difference between the two types of licensing. On the one hand, targeted licensing allows one downstream firm to *gain a cost advantage* over its rival, and thus to benefit from strong demand and a large markup. On the other hand, market-wide licensing allows each downstream firm to *avoid facing a cost disadvantage* relative to its rival, a situation which would yield weak demand and a small markup. This in turn helps explain the key results of the paper, which we present below.

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Note that $\Delta_T$ has no impact on Firm 1’s no-access profits: $\partial \pi_1 (0, 0, \theta) / \partial \Delta_T = 0$. 

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3.1 Optimal Licensing Strategy

A key difference between the two licensing strategies concerns the way in which competition affects the innovator’s licensing payoffs. Indeed, as is evident from Lemmas 1 and 2:

**Proposition 1** The innovator’s equilibrium payoff under market-wide licensing, \( Z^*_M = \frac{2}{(9 + 2\theta)} - h \), is strictly decreasing in competition. In contrast, the equilibrium payoff under targeted licensing, \( Z^*_T = \frac{1}{18 - 2\theta} \), is strictly increasing in competition. Thus competition unambiguously increases the appeal of targeted licensing relative to market-wide licensing.

To see the intuition behind these results, consider the impact of competition on the market-wide licensing payoff \( Z^*_M \) and on the targeted licensing payoff \( Z^*_T \), respectively:

\[
\frac{\partial Z^*_M}{\partial \theta} = \sum_{i=1}^{2} \frac{\partial z^*_i (\Delta_M, \theta)}{\partial \theta} = \sum_{i=1}^{2} \frac{\partial [\pi_i (\Delta_M, \Delta_M, \theta) - \pi_i (0, \Delta_M, \theta)]}{\partial \theta} \\
= \sum_{i=1}^{2} \left[ \frac{\partial P_i (\Delta_M, \Delta_M, \theta)}{\partial \theta} d_i (\Delta_M, \Delta_M, \theta) - \frac{\partial P_i (0, \Delta_M, \theta)}{\partial \theta} d_i (0, \Delta_M, \theta) \right] \\
+ \sum_{i=1}^{2} \left[ -\frac{\partial d_i (0, \Delta_M, \theta)}{\partial \theta} P_i (0, \Delta_M, \theta) \right] \tag{11}
\]

and:

\[
\frac{\partial Z^*_T}{\partial \theta} = \frac{\partial z^*_1 (\Delta_T, \theta)}{\partial \theta} = \frac{\partial [\pi_1 (\Delta_T, 0, \theta) - \pi_1 (0, 0, \theta)]}{\partial \theta} \\
= \left[ \frac{\partial P_1 (\Delta_T, 0, \theta)}{\partial \theta} d_1 (\Delta_T, 0, \theta) - \frac{\partial P_1 (0, 0, \theta)}{\partial \theta} d_1 (0, 0, \theta) \right] \\
+ \left[ -\frac{\partial d_1 (\Delta_T, 0, \theta)}{\partial \theta} P_1 (\Delta_T, 0, \theta) \right]. \tag{12}
\]

Competition affects the innovator’s licensing payoffs in two primary ways. First, it induces firms to lower their prices: using expression (24), one can see that regardless of the values of \( \Delta_i \) and \( \Delta_j \), \( \frac{\partial P_i (\Delta_i, \Delta_j, \theta)}{\partial \theta} = -1/\theta^2 < 0 \). This is the *rent reduction effect* of competition. The first square bracket in (11) and (12) captures the impact of rent reduction on the licensor’s payoff. Consider market-wide licensing, for example. It follows directly from above that the negative impact of competition on a downstream firm’s price-cost margins is independent of whether that firm has access to the innovation

\[\text{From the envelope theorem, we know that the impact of competition on the licensor’s payoff that occurs through changes in innovation levels is null in equilibrium. Moreover, competition has no impact on equilibrium demand when firms have symmetric costs: } \frac{\partial d_i (\Delta, \Delta, \theta)}{\partial \theta} = 0.\]

\[\text{For a discussion of the effects of product market competition on profit differentials in the context of entrepreneurial finance, see Bettignies and Duchêne (2015).}\]
or not: $\partial P_i (\Delta_M, \Delta_M, \theta) / \partial \theta = -1/\theta^2 = \partial P_i (0, \Delta_M, \theta) / \partial \theta$. However, the overall impact on the firm’s symmetric profits is more negative than on its laggard profits, because in the former case the decrease in margin affects a larger equilibrium demand: $d_i (\Delta_M, \Delta_M, \theta) = 1/2 > 1/2 - \theta \Delta_M / 6 = d_i (0, \Delta_M, \theta)$. Overall, the impact of rent reduction on the firm’s willingness to pay for the license and on the innovator’s payoff is $-\Delta_M / (6 \theta)$. Similarly, under targeted licensing, the impact of rent reduction on the innovator’s payoff is $-\Delta_T / (6 \theta)$.\(^{18}\)

The second key effect of competition on the innovator’s licensing payoff is to increase (resp. decrease) demand for the firm with a cost advantage (resp. disadvantage): $\partial d_i / \partial \theta = (\Delta_i - \Delta_j) / 6 \geq 0$ iff $\Delta_i \geq \Delta_j$, and $\partial d_i / \partial \theta = 0$ iff $\Delta_i = \Delta_j$. This is the business stealing effect of competition. The second square bracket in (11) and (12) captures the impact of business stealing on the licensor’s payoff. Consider market-wide licensing again. The positive (resp. negative) effect of competition on demand for firms with an innovation advantage (resp. disadvantage) relative to their rivals has no impact on a downstream firm’s symmetric profits, since in that case $\Delta_{1M}^* = \Delta_{2M}^*$. But in the case of laggard profits, the firm is at an innovation disadvantage relative to its rival, which translates into a demand disadvantage. Competition exacerbates this disadvantage by reducing demand for that firm. Accordingly, by worsening the firm’s laggard profits, business stealing increases the firm’s willingness to pay for the license, and the innovator’s payoff by $-\partial d_i (0, \Delta_M, \theta) / \partial \theta = \Delta_{1M}^* / (6 \theta) - (\Delta_{1M})^2 / 18 > 0$. Under targeted licensing, access to the innovation gives Firm 1 an innovation advantage over Firm 2, which translates into leader profits. Competition augments this advantage by increasing demand for that firm. This in turn raises Firm 1’s willingness to pay for the license, and the innovator’s payoff by $\partial d_i (\Delta_T, 0, \theta) / \partial \theta = \Delta_T / (6 \theta) + (\Delta_T)^2 / 18 > 0$.

Clearly, under market-wide licensing the impact of rent reduction dominates the impact of business stealing, and competition strictly decreases the innovator’s licensing payoff; while in contrast under targeted licensing the impact of business stealing dominates, and competition strictly increases the innovator’s licensing payoff. Indeed, competition increases the appeal of targeted licensing relative to market-wide licensing for the innovator.

This difference in effects of competition on licensing payoff comes primarily from business stealing. Under market-wide licensing, business stealing increases a firm’s willingness to pay by worsening demand if the license is not purchased, a situation in which the firm is at an innovation disadvantage

\(^{18}\)The intuition is the same as under market-wide licensing. Competition puts downward pressure on price-cost margins, in both leader and symmetric cases; but the overall impact is more negative on leader profits than on symmetric profits, because in the former case the decrease in margin affects a larger equilibrium demand. Hence the negative impact of rent reduction on willingness to pay for the license.
and hence makes relatively small margins. Thus the negative impact of decreased demand on the
licensee’s laggard profits, and the resulting positive effect on his willingness to pay for the license, is
relatively small, too small in fact to offset the negative impact of rent reduction on his willingness
to pay. In contrast under targeted licensing, business stealing works by increasing the firm’s demand
and profits if the license is purchased, a situation in which the firm is at an innovation advantage
and hence makes relatively large margins. Accordingly the positive impact of increased demand on
the firm’s leader profits, and hence on its willingness to pay for the license, is relatively large, large
enough to offset the negative impact of rent reduction.

The innovator’s optimal licensing strategy then follows directly from the preceding analysis. To see
this, recall from Lemmas 1 and 2 that \( Z_M^* = \frac{2}{(9+2\theta)} - h \) and \( Z_T^* = \frac{1}{18-20} \) for all \( \theta \in \Theta \). It then follows
that \( \lim_{\theta \to 0} Z_T^* - Z_M^* = -1/6 + h \) and that \( \lim_{\theta \to 9/2} Z_T^* - Z_M^* = h \); and together with Proposition 1 this
immediately yields the following result regarding the impact of competition on equilibrium licensing
strategy:

**Proposition 2** If the exogenous (relative) cost of market-wide licensing \( h \) is low to moderate - \( h \in (0, 1/6) \) - there exists a threshold level of competition \( \theta^* (h) \in \Theta \), with \( \theta^* (h) / \theta < 0 \), such that the
innovator chooses market-wide licensing for all \( \theta \in (0, \theta^* (h)) \), and chooses targeted licensing for all
\( \theta \in [\theta^*, 9/2) \). If \( h \) is high - \( h \geq 1/6 \) - targeted licensing is the optimal choice for the innovator for all
\( \theta \in \Theta \).

[Insert Figure 1 here.]

Thus, while competition unambiguously increases the appeal of targeted licensing relative to
market-wide licensing (Proposition 1), as stated in Proposition 2 and depicted in Figure 1 this may
or may not lead to a switch in licensing strategy, depending on the value of the exogenous cost \( h \).

Our view is that in practice, while the additional transaction costs associated with market-wide
licensing do exist, they are not so great as to eliminate this licensing strategy as an optimal choice
regardless of the degree of competition. Accordingly, our prediction is that competition will have an
impact on the innovator’s licensing strategy, leading to a switch from market-wide licensing to targeted
licensing. We test this prediction empirically in Section 4.

Note from Proposition 2 that the threshold level of competition \( \theta^* (h) \) at which the innovator
switches from market-wide licensing to targeted licensing is strictly decreasing in the exogenous cost
of market-wide licensing: \( \partial \theta^* (h) / \partial h < 0 \). Intuitively, the greater the cost of market-wide licensing, the “sooner” the innovator will switch to targeted licensing at competition intensifies.

Also note that our result that downstream competition (measured by the degree of substitutability between products) may lead the upstream innovator to reduce the number licenses is consistent with Bagchi (2008), which illustrated a similar result albeit in a different context of licensing auctions and differentiated downstream Cournot markets. What is more novel here is our use of this result to improve our understanding of the interaction between downstream competition and upstream innovation. This is the purpose of our analysis below.

### 3.2 Optimal Innovation Strategy

#### 3.2.1 Licensing and Innovation

A key difference between the two licensing strategies concerns the way in which competition affects equilibrium innovation. Indeed, it is immediately clear from lemmas 1 and 2 that:

**Proposition 3** Equilibrium innovation under market-wide licensing, \( \Delta^*_M = \frac{6}{9 + 2 \theta} \), is strictly decreasing in competition. In contrast, equilibrium innovation under targeted licensing, \( \Delta^*_T = \frac{3}{9 - 3 \theta} \), is strictly increasing in competition. Moreover, there exists a threshold level of competition \( \theta^{**} = 9/4 \) such that \( \Delta^*_T < \Delta^*_M \) for all \( \theta \in (0, \theta^{**}) \) and \( \Delta^*_T \geq \Delta^*_M \) for all \( \theta \in [\theta^{**}, 9/2) \).

To understand the intuition behind these results, let us first use (31) and (27), and (8) and (10), to derive the marginal impact of innovation on the innovator’s licensing revenue, under market-wide licensing and targeted licensing, respectively:

\[
\sum_{i=1}^{2} \frac{\partial z_{1i}(\Delta_M, \theta)}{\partial \Delta_M} = \sum_{i=1}^{2} \left[ -\frac{\partial \pi_i}{\partial \Delta_j}(0, \Delta_M, \theta) \right] = \sum_{i=1}^{2} \left[ -\frac{\partial d_i}{\partial \Delta_j}(\theta) P_i(0, \Delta_M, \theta) - \frac{\partial P_i}{\partial \Delta_j} d_i(0, \Delta_M, \theta) \right] = \sum_{i=1}^{2} \left[ \frac{\theta}{6} P_i(0, \Delta_M, \theta) + \frac{1}{3} d_i(0, \Delta_M, \theta) \right],
\]

---

\( \text{19} \)The threshold value \( \theta^{**} = 9/4 \) is obtained simply by solving \( \Delta^*_M = \frac{6}{9 + 2 \theta} = \frac{3}{9 - 3 \theta} = \Delta^*_T \) for \( \theta \).
and:

\[
\frac{\partial z_{1T}(\Delta_T, \theta)}{\partial \Delta_T} = \frac{\partial \pi_1}{\partial \Delta_1}(\Delta_T, 0, \theta) \\
= \frac{\partial d_1}{\partial \Delta_1}(\theta) P_1(\Delta_T, 0, \theta) + \frac{\partial P_1}{\partial \Delta_1} d_1(\Delta_T, 0, \theta) \\
= \frac{\theta}{6} P_1(\Delta_T, 0, \theta) + \frac{1}{3} d_1(\Delta_T, 0, \theta).
\]

Consider the innovator’s market-wide licensing revenue from Firm \( i \). Increasing innovation \( \Delta_M \) increases Firm \( i \)’s willingness to pay for the innovation by increasing the cost advantage that its rival Firm \( j \) will have if it does not license the innovation - in other words it decreases Firm \( i \)’s laggard profits. It does so in two ways. First, the increase in Firm \( j \)’s cost advantage enables that firm to steal market share at the expense of Firm \( i \): \( \frac{\partial d_j}{\partial \Delta_j}(\theta) = \frac{\theta}{6} > 0 \) and \( \frac{\partial d_i}{\partial \Delta_j}(\theta) = -\frac{\theta}{6} < 0 \); and the impact on Firm \( i \)’s laggard profits is the margin-adjusted marginal change in expected demand, \( \frac{\partial d_i}{\partial \Delta_j}(\theta) P_i(0, \Delta_M, \theta) < 0 \).

Second, the increase in Firm \( j \)’s cost advantage enables that firm to increase its price-cost margin in equilibrium, and forces a smaller price-cost margin (through lower equilibrium price) onto Firm \( i \):

\[
\frac{\partial P_i}{\partial \Delta_j} = \frac{1}{3} > 0 \quad \text{and} \quad \frac{\partial P_j}{\partial \Delta_j} = -\frac{1}{3} < 0;
\]

and the impact on Firm \( i \)’s laggard profits is the demand-adjusted marginal change in price-cost margin, \( \frac{\partial P_i}{\partial \Delta_j} d_i(0, \Delta_M, \theta) < 0 \).

Next, consider targeted licensing revenue from Firm 1. Here in contrast, increasing innovation \( \Delta_T \) increases Firm 1’s willingness to pay for the innovation by increasing the cost advantage that it will have over Firm 2 if it does license the innovation - in other words it increases Firm 1’s leader profits. Again, this works in two ways. First, the increase in Firm 1’s cost advantage enables that firm to steal market share from Firm 2 \( \frac{\partial d_1}{\partial \Delta_1}(\theta) = \frac{\theta}{6} > 0 \); increasing Firm 1’s leader profits by \( \frac{\partial P_1}{\partial \Delta_1}(\theta) P_1(\Delta_T, 0, \theta) > 0 \). Second, the increase in Firm 1’s cost advantage leads to a higher price-cost margin for that firm \( \frac{\partial P_1}{\partial \Delta_1} = \frac{1}{3} > 0 \); increasing Firm 1’s leader profits by \( \frac{\partial P_1}{\partial \Delta_1} d_1(\Delta_T, 0, \theta) > 0 \).

Now, differentiating (13) and (14) with respect to \( \theta \), we derive the effects of competition on the innovator’s marginal benefit (in terms of licensing revenue) from innovation, under market-wide licensing and targeted licensing, respectively:

\[
\sum_{i=1}^{2} \partial \left[ -\frac{\partial \pi_i(0, \Delta_M, \theta)}{\partial \Delta_j} \right] / \partial \theta = \sum_{i=1}^{2} \left[ \frac{\partial d_i(0, \Delta_M, \theta)}{\partial \theta} \right] + \left[ -\frac{\partial P_i}{\partial \Delta_j} \right] P_i(0, \Delta_M, \theta) \left[ -\frac{\partial d_i}{\partial \Delta_j} \right],
\]
and:

$$\frac{\partial \left[ \frac{\partial \pi_1 (\Delta_T, 0, \theta)}{\partial \Delta_1} \right]}{\partial \theta} = \frac{\partial d_1 (\Delta_T, 0, \theta)}{\partial \theta} \left[ \frac{\partial P_1}{\partial \Delta_1} \right] + \frac{\partial P_1 (\Delta_T, 0, \theta)}{\partial \theta} \left[ \frac{\partial d_1}{\partial \Delta_1} \right] + \frac{\partial^2 d_1}{\partial \Delta_1 \partial \theta} P_1 (\Delta_T, 0, \theta).$$ (16)

The degree of competition $\theta$ - by making consumers more sensitive to prices relative to their position on the Hotelling line - has three effects on the marginal impact of innovation on licensing revenue.\(^{20}\) As shall now become clear below, the forces at work are very similar to the ones shown above to affect licensing revenues.

The first factor in (15) and (16) captures the *business stealing effect of competition* on the marginal licensing revenue from innovation. Consider market-wide licensing: by reducing laggard demand for Firm 1, this effect mitigates the reduction in Firm 1’s laggard profits resulting from the drop in price-cost margin associated with an increase in innovation $\Delta_M$ in Firm 2. It therefore mutes Firm 1’s increased willingness to pay for the license and reduces the innovator’s marginal benefit from innovation.\(^{21}\) In contrast, under targeted licensing, by increasing leader demand for Firm 1, this effect amplifies the increase in leader profits resulting from the increase price-cost margin associated with an increase in innovation $\Delta_M$ in Firm 1. Thus under targeted licensing this exacerbates Firm 1’s increased willingness to pay and increases the innovator’s marginal benefit from innovation.

The second factor in (15) and (16) captures the *rent reduction effect* of competition on the marginal licensing revenue from innovation. Under market-wide licensing, the price reduction associated with more intense competition mitigates the reduction in Firm 1’s laggard profits resulting from the drop in laggard demand associated with an increase in innovation $\Delta_M$ in Firm 2. It therefore mutes Firm 1’s increased willingness to pay for the license. Under targeted licensing, the price reduction mitigates the increase in Firm 1’s leader profits resulting from the increase in leader demand associated with an increase in innovation $\Delta_T$, thus dampening Firm 1’s increased willingness to pay. Thus under both licensing strategies, this effect reduces the marginal benefit from innovation.

The third factor in (15) and (16) captures an effect we have not discussed yet: the *increased business stealing effect of competition* (Baggs and Bettignies, 2007), which has a positive impact on the marginal product of innovation.\(^{22}\) Under market-wide licensing, this effect exacerbates the decrease

\(^{20}\)Note from above that $\frac{\partial P_1}{\partial \Delta_1} = \frac{1}{3}$ and $\frac{\partial P_1}{\partial \Delta_T} = -\frac{1}{3}$ are independent of competition $\theta$, and hence $\frac{\partial^2 P_1}{\partial \Delta_1 \partial \theta} = \frac{\partial^2 P_1}{\partial \Delta_T \partial \theta} = 0$.

\(^{21}\)This effect is related to what Gosh et al. (2015) call “share-reduction effect” in the context of continuous improvement versus discrete innovation.

\(^{22}\)While the direct business stealing effect of competition affects the *levels* of demand associated with given levels of innovation, in contrast the increased business stealing effect of competition affects the *changes* in demand associated with an innovation increase.
in Firm $i$’s laggard demand - and hence exacerbates Firm $i$’s increased willingness to pay for a license - associated with an increase in innovation $\Delta_M$. Under targeted licensing, this effect amplifies the increase in Firm 1’s leader demand associated with an increase in $\Delta_T$, hence magnifying its increased willingness to pay for the license. Accordingly, under both licensing strategies, this effect increases the innovator’s marginal benefit from innovation.

Using (24) to determine the magnitude of each of these effects, one can easily verify that the differential effects of competition on innovation across licensing strategies comes primarily from differences in increased business stealing. Under market-wide licensing, the impact of increased business stealing simplifies to $\left[-\frac{\partial^2 d_i}{\partial M \partial \theta}\right]P_1(0, \Delta_M, \theta) = 1/(6\theta) - \Delta_M/18 > 0$. This effect is relatively weak, in the sense that it fails to outweigh the negative impact of rent reduction, which simplifies to $\frac{\partial d_i(0, \Delta_M, \theta)}{\partial \theta} = -1/(6\theta) < 0$. Together these two effects imply a negative impact of competition on the marginal benefit from innovation; and the business stealing effect, which simplifies to $\frac{\partial d_i(0, \Delta_M, \theta)}{\partial \theta} = -\Delta_M/18 < 0$, exacerbates this negative impact. Thus, under market-wide competition decreases the innovator’s marginal benefit from innovating, thereby reducing equilibrium innovation $\Delta^*_M$.

In contrast, under targeted licensing, the impact of increased business stealing can be shown to simplify to $\frac{\partial^2 d_i}{\partial \Delta_T \partial \theta}P_1(\Delta_T, 0, \theta) = 1/(6\theta) + \Delta_T/18 > 0$. It is relatively strong in that is does outweigh the negative impact of rent reduction (which itself is the same under both licensing strategies), $\frac{\partial d_i(\Delta_T, 0, \theta)}{\partial \theta} \left[\frac{\partial d_i}{\partial \Delta_T}\right] = -1/(6\theta)$. Together these two effects imply a positive impact of competition on the marginal benefit from innovation; and the business stealing effect, which simplifies to $\frac{\partial d_i(\Delta_T, 0, \theta)}{\partial \theta} \left[\frac{\partial d_i}{\partial \Delta_T}\right] = \Delta_T/18 > 0$, accentuates this positive impact. Indeed, under targeted licensing, competition raises the innovator’s marginal benefit from innovating, thereby increasing equilibrium innovation $\Delta^*_T$.

Note that the differential strength of increased business stealing across licensing strategies comes from the difference underlined at the beginning of Section 3. Under market-wide licensing, increased business stealing exacerbates the decrease in Firm $i$ laggard demand associated with an increase in innovation $\Delta_M$. But in the laggard situation where Firm $i$ does not purchase the license, it is left with an innovation disadvantage relative to its rival, and relatively low margins in equilibrium, thus muting the exacerbating effect of increased business stealing. In contrast, under targeted licensing, increased business stealing amplifies the increase in Firm 1’s leader demand associated with an increase in $\Delta_T$. This is a situation in which Firm 1 has an innovation advantage relative to its rival, and relatively
high margins in equilibrium, further magnifying the amplifying effect of increased business stealing.

### 3.3 Competition and Innovation in Equilibrium

Bringing together the results of Propositions 2 and 3, one can easily deduce the impact of competition on equilibrium innovation:

**Proposition 4** If the relative cost of market-wide licensing $h$ is low to moderate - $h \in (0, 1/6)$ - then for all $\theta \in (0, \theta^* (h))$ innovation $\Delta^* = \Delta^*_M$ is strictly decreasing in competition, and for all $\theta \in [\theta^*, 9/2)$ innovation $\Delta^* = \Delta^*_T$ is strictly increasing in competition. If $h$ is high - $h \geq 1/6$ - innovation $\Delta^* = \Delta^*_T$ is strictly increasing in competition for all $\theta \in \Theta$.

The intuition follows directly from the discussions of Propositions 2 and 3. We depict the results of Proposition 4 in Figure 2 below:

*[Insert Figure 2 here.]*

Note that when the relative cost of market-wide licensing $h$ is low to moderate - $h \in (0, 1/6)$ - equilibrium innovation may jump up or down depending on the value of $h$. To see this, first recall from Proposition 3 that there exists a threshold level of competition $\theta^{**} = 9/4$ such that innovation is greater under market-wide licensing for all $\theta \in (0, \theta^{**})$, and greater under targeted licensing for all $\theta \in [\theta^{**}, 9/2)$. Now if $h$ is at the low end of $(0, 1/6)$, then market-wide licensing is relatively attractive, and the threshold level of competition $\theta^* (h)$ at which the innovator switches from market-wide licensing to targeted licensing is relatively high, higher in fact than $\theta^{**} = 9/4$. In this case innovation jumps up at $\theta^* (h)$. Conversely, if $h$ is at the high end of $(0, 1/6)$, then market-wide licensing is relatively unattractive, and $\theta^* (h)$ is relatively low and lower than $\theta^{**} = 9/4$. In that case innovation jumps down at $\theta^* (h)$.

At a broader level, the foregoing analysis suggests that the relationship between downstream innovation and upstream innovation is inextricably linked to the innovator’s licensing strategy. Indeed, the key empirical implication of Proposition 4 and Figure 2 is that as long as the transaction costs associated with market-wide licensing are not prohibitively high, we should observe an U-shaped relationship between downstream competition and upstream innovation; with innovation decreasing in competition at low levels of competition (when market-wide licensing is optimal), and increasing in competition at high levels of competition (when targeted licensing is optimal). We test this empirical prediction in the next section.
4 Empirical Implications and Implementation

As discussed above, our theoretical model points to a threshold level of downstream product market competition such that above (below) that threshold, targeted (market-wide) licensing is optimal, and downstream competition increases (decreases) upstream innovators’ incentives to innovate. In particular, the insights of our theoretical model yield the following three empirical predictions: (1) There is an U-shaped relationship between downstream competition and upstream innovation. (2) Downstream competition increases the appeal of targeted licensing relative to market-wide licensing for the upstream innovator. (3) Under targeted (market-wide) licensing strategy, upstream innovation increases (decreases) in downstream competition.

To test these implications, we first investigate empirically how downstream competition affects upstream innovation in Section 4.1. Within this section, we outline the structure of our regressions; report our empirical results; present our robustness checks; and address potential endogeneity concerns. Second, we examine how downstream competition influences upstream innovators’ choice of licensing strategy in Section 4.2 where, after briefly introducing the data on licensing deals based on the SDC database, we present and discuss our empirical results.

4.1 Downstream Competition and Upstream Innovation

4.1.1 Empirical Model Specification

To analyze how downstream competition affects upstream innovation, we follow the literature on competition and innovation (e.g. Aghion et al., 2005) to use flexible nonlinear estimators. Specifically, given that patent data generally do not satisfy the Poisson assumption of equal mean and variance, we choose Negative Binomial model to estimate the relationship between downstream competition and upstream innovation (Hashmi, 2013). The specification below is motivated by the prediction of an U-shaped relationship between downstream competition and upstream innovation:

\[
CITE\_WEIGHT\_PAT_{i,j,t} = \beta_0 + \beta_1 \cdot C_{j,t} + \beta_2 \cdot C_{j,t}^2 + \gamma \cdot Z_{i,t} + \delta_t + \alpha_j + \epsilon_{i,j,t},
\]

where \(CITE\_WEIGHT\_PAT_{i,j,t}\) is the citation-weighted patent counts that firm \(i\) in industry \(j\) has in year \(t\), which captures upstream firm innovation level. Compared with patent counts or citations per patent, weighting patent counts by their citations can reflect the heterogeneous value of patents and
hence is considered to be a better proxy for firms’ innovation quality (Aghion et al., 2005). Therefore, we choose to use citation-weighted patent counts as our main dependent variable in the baseline model. In addition, we also use citations per patent and total citations that firm \( i \) has in year \( t \) as proxies for upstream firm innovation in alternative regressions for robustness check. Moreover, our main explanatory variable of interest, downstream competition, denoted by \( C_{j,t} \), represents the average product market competition of all the downstream industries that relate to the upstream industry \( j \) in which firm \( i \) operates in year \( t \), i.e. \( C_{j,t} = \frac{\sum C_{j,k,t}}{n_{j,t}} \), where \( C_{j,k,t} \) is the competition level in a downstream industry \( k \) related to the upstream industry \( j \) in year \( t \), and \( n_{j,t} \) is the number of downstream industries related to the upstream industry \( j \) in year \( t \). Finally, we include \( Z_{i,t} \), \( \delta_t \), and \( \alpha_j \) as our control variables in the model specification. Among them, \( Z_{i,t} \) is a vector of the firm characteristics; \( \delta_t \) represents year fixed effects and controls for changes in the macroeconomic environment and systematic changes in patenting activities over time; industry fixed effects, \( \alpha_j \), based on five-digit NAICS industry dummies, controls for any unobserved industry heterogeneity that is time invariant and affects firm patenting activities.

Model (17) allows us to estimate the non-linear impact of downstream industry competition on upstream firm innovation. To see this, let us differentiate \( CITE\_WEIGHT\_PAT_{i,j,t} \) with respect to \( C_{j,t} \), which yields \( \frac{\partial CITE\_WEIGHT\_PAT_{i,j,t}}{\partial C_{j,t}} = \beta_1 + 2\beta_2 C_{j,t} \). An important implication from our theoretical model is that there is non-monotonic U-shaped relationship between downstream competition and upstream innovation. Therefore, it suggests that the signs of \( \beta_1 \) and \( \beta_2 \) are expected to be negative and positive respectively. In other words, when there is a low level of competition in the downstream industry, i.e. \( C_{j,t} \) is small, \( 2\beta_2 C_{j,t} \) is expected to be positive and small; small enough in fact for the net marginal impact of downstream competition, \( \beta_1 + 2\beta_2 C_{j,t} \), to be negative. In contrast, when downstream competition intensifies enough, i.e. \( C_{j,t} \) is large and \( 2\beta_2 C_{j,t} \) is expected to be positive and large, then the net marginal impact of downstream competition, \( \beta_1 + 2\beta_2 C_{j,t} \), to be positive. Taken together, we expect the coefficients of downstream competition and its squared term, \( \beta_1 \) and \( \beta_2 \), to be negative and positive respectively, indicating an U-shaped relationship between downstream competition and upstream firm innovation.

4.1.2 Data Sample and Summary Statistics

Data Sample

The dataset we built for our study is determined by the joint availabilities of data on innovation,
competition, upstream-downstream relationships, and licensing deals from the following five different sources.

Firstly, to measure innovating activities, we obtain data from the National Bureau of Economic Research (NBER) Patent Citation Database which was initially created by Hall, Jaffe, and Trajtenberg (2001, 2005). This database contains annual information on patents and citations for publicly traded U.S. firms over the period 1976 – 2006. The variables in the dataset include patent number, patent assignee, number of citations made, number of citation received, patent application year and grant year, and so forth. We use these variables to construct citation-weighted patent counts, citations per patent, and total patent citations to proxy upstream firm innovation respectively.

Second, we collect financial data from Standard and Poor’s Compustat Annual Files to compute downstream industry competition and obtain control variables as well. Specifically, we obtain data on firm sales, operating profits, gross profit margin, financial costs, and industry code where proxies of industry competition based on the Lerner index can be computed. We also collect a vector of control variables about firm and industry characteristics from Compustat, which may affect firms’ innovation activity or licensing strategy.

Third, to identify upstream and downstream industry relationship, we hand-collect data from 2008 IBISWorld reports (Hui, Klasa, and Yeung, 2012). IBISWorld is an independent publisher of U.S. industry research, and its annual reports use a variety of sources from government, company, to industry association statistics, providing information about market characteristics, supply-chain relationships, and so forth. We use the information about supply-chain relationships to identify the downstream industries for each five-digit NAICS industry. Specifically, we hand-collect the data on all five digit NAICS industries and their downstream industries; record the data into excel spreadsheet; we then have our data on upstream-downstream relationships ready for analysis. Table 1 presents the average number of five-digit NAICS downstream industries for each two-digit NAICS upstream industry group. Among these industry groups, manufacturing sectors have on average the greatest number of downstream industries (134.5), while accommodation and food Services has on average the fewest downstream industries (8).

Fourth, we obtain data on firms’ licensing strategies from the Joint Venture & Strategic Alliance database of Securities Data Company (SDC). We choose to use SDC for the reason that it provides detailed information on licensing deals across a variety of industry sectors, which is especially well-suited for our research on downstream industry competition and upstream innovation. Specifically, we
carefully read deal descriptions for each licensing deal to identify who the licensors and the licensees are, whether the licensing strategies are exclusive, nonexclusive, or cross-licensing, and the SIC codes of the participants and alliance. Notice that by definition exclusive and non-exclusive licensing strategies in SDC database are analogue to the targeted licensing and market-wide licensing in our theoretical model respectively.

Finally, we obtain import tariff data from Peter Schott’s International Economics Resource Page to address the potential endogeneity of downstream industry competition (Schott, 2010). This Web Page provides the data on imports by country and industry from 1989 – 2005. We collect the import tariff rates for all industries in the dataset and then calculate reductions in import tariff rates for each industry in each year. We expect to use reductions in import tariff rates as an exogenous competitive shock to address the potential endogeneity concerns for downstream competition.

[Insert Table 1 here.]

**Summary Statistics**

We present a summary statistics of the U.S. data in Table 2. All data are annual. The time coverage of the U.S. data is over the period 1976 – 2006 (31 years). At five-digit NAICS level, there are 319 industries with 24,845 firm - year observations. In order to mitigate the impact of outliers, we winsorize all variables at the 1st and 99th percentiles.

Panel B of Table 2 presents means, medians, standard deviations, 10th and 90th percentiles for upstream firm innovation, downstream industry competition, and control variables. In terms of upstream firm innovation, we calculate the number of patents that cite a given patent based on all U.S. granted patents by 2006. The parenting activities in our sample show typical skewness with a mean of 0.1362 citation-weighted patent counts and a median of 0.00239. Related measure citations per patent has a mean of 15.548 and a median of 10.485 which suggests that each patent has on average 15.548 cites.

The summary statistics for downstream competition in Panel B of Table 2 indicates that downstream industry competition based on Lerner index has an average of 0.7687 and a median of 0.779. And the standard deviation of downstream competition is 0.0699 across all the industries in U.S. from 1976 - 2006. Regarding other variables of interest, the average firm in our sample has a market-to-book ratio of 1.458, a R&D to assets ratio of 5.165%, a leverage ratio of 18.62%, capital expenditures over total assets of 5.03%, and return on asset of 0.121. The upstream industry competition based on Herfindahl has an average of 0.848 and a median of 0.601.
4.1.3 Variable Construction

**Measures of Upstream Innovation** Firm level innovation is often captured by R&D expenditures and patenting activity. Patenting activity measures innovation output and captures how effectively a firm has utilized its innovation inputs. In contrast, R&D expenditures measure the observable innovation input of firms and therefore hard to capture the actual quality of firm innovation. Hence, patenting activity is usually considered to be a better proxy for firm innovation in the relevant literature (Chemmanur and Tian, 2013). Accordingly, to construct our firm-level innovation measure, we calculate the average patents that each firm has within a year, and to reflect the heterogeneous of patents, we weight each patent by the number of times it has been cited by other patents. All the patent data is obtained from NBER Patent Citation Database. And our sample includes all firms across all industries over the period 1976 – 2006. We use information on citations to and from each patent to construct a count of citation-weighted patent counts. Specifically, we firstly calculate the total number of patents firm $i$ has in year $t$, and then calculate the weight of firm $i$’s patents by using the patent citations that firm $i$ has received divided by the total patent citations that all sample firms have received in year $t$, and we then get citation-weighted patent counts for firm $i$ in year $t$,

$$CITE\_WEIGHT\_PAT_{i,t} = \frac{\sum_p Patent\_Counts_{i,t} \cdot \frac{\sum_P Patent\_Citations_{i,p,t}}{\sum_i \sum_p Patent\_Citations_{i,p,t}}}{\sum_i \sum_p Patent\_Citations_{i,p,t}},$$

where subscripts $i$, $p$, and $t$ denote firm, patent, and year respectively; $Patent\_Counts_{i,t}$ represents the total patent counts that firm $i$ has in year $t$; $Patent\_Citations_{i,p,t}$ means the citations that firm $i$’s patent $p$ has received in year $t$.

Furthermore, we adjust our measure of innovation to address the truncation problem arising as the patents appear in the database only after they are granted. We correct for the truncation related to the citation counts as a patent can keep receiving citations over a long period of time, but we only observe citations received up to 2006. Follow Hall, Jaffe, and Trajtenberg (2001, 2005), we correct this truncation bias by dividing the observed citation counts by the fraction of predicted lifetime citations actually observed during the lag interval. More specifically, we scale up the citation counts using the variable “hjtwt” provided by the NBER Patent Citation Database, which relies on the shape of the citation lag distribution. The truncation-adjusted measures of patents and citation counts are used in
all of our tests.

We also use another two alternatives to proxy for upstream firm innovation: citations per patent and total patent citations. Specifically, we calculate them as follows respectively: 

\[ CITE\_PER\_PAT_{i,t} = \frac{\sum_p Patent\_Citations_{i,p,t}}{Patent\_Counts_{i,t}}; \]

\[ CITE\_TOTAL_{i,t} = \sum_p Patent\_Citations_{i,p,t}. \]

**Proxies for Downstream Competition**  In the empirical IO literature, Herfindahl index and the market measure of competition based on Lerner index are among the most popular ones to measure industry competition level. Due to the fact that Herfindahl index cannot capture changes in firms’ conduct in reallocating markets shares between firms (Boone, 2007), and it is usually hard to clearly define a market, we choose to use one minus the Lerner index to proxy industry competition level. Higher value of one minus Lerner index means higher level of industry competition. In particular, the market measure of competition is defined as 

\[ C_{j,t} = 1 - \frac{\sum_{i=1}^{n_j} L_{i,t}}{n_j}, \]

where \( j \) denotes the industry and \( i \) denotes a firm in the industry. As in Aghion et al. (2005), Lerner index, \( L_{i,t} \), is computed as 

\[ L_{i,t} = \frac{Operating\_profit - Financial\_cost}{Sales}, \]

i.e., we use operating profits net of depreciation provisions and an estimated financial cost of capital divided by sales to measure the price cost margin. We collect relevant data from Compustat database. In order to compute the competition level across all the firms in an industry, we use the entire sample of Compustat in each industry, not only those in the patenting subsample.

**Measuring Control Variables**  We control for a vector of firm and industry characteristics that may affect a firm’s future innovation productivity. All variables are computed for firm \( i \) over its fiscal year \( t \). In the baseline regressions, the control variables include profitability, \( ROA \), measured by return on assets; investment in innovation, \( RDTA \), measured by R&D expenditures scaled by total assets; leverage, \( LEV \), measured by total debt-to-total assets; investment in fixed assets, \( CAPETA \), measured by capital expenditures scaled by total assets; growth opportunity, \( MB \), measured by Tobin’s Q. To mitigate nonlinear effects of horizontal product market competition (Aghion et al., 2005), we also include upstream product market competition and its squared term, \( UP\_COMP \) and \( UP\_COMP\_SQUARE \), in our baseline regressions; \( UP\_COMP \) is measured by the Herfindahl index based on annual sales; Detailed variable definitions are described in Panel A of Table 2.

**4.1.4 Empirical Results**

**Downstream Competition and Upstream Innovation**
We report the empirical results in Table 3. All the standard errors in our regressions in Table 3 are adjusted and clustered at the firm level.

In our baseline model, we choose Negative Binomial model to investigate the impact of downstream industry competition on upstream firm innovation (Hashmi, 2013). We also control for year and industry fixed effects in the estimation. Our consideration is that if both innovation and competition are related to the business cycle or some other variable that changes over time, then we might overestimate the relationship between downstream competition and upstream firm innovation. Furthermore, different industries have different propensities to innovate. Hence, it is possible to see a lot of variation in innovative activity across industries that may not be due to variation in downstream industry competition. Indeed, some institutional features of industries may affect the innovating activities of firms in those industries. Therefore, we use year and industry fixed effects to control for these problems.

In column (1) of Panel A, the coefficients of downstream industry competition and its squared term are -8.541 and 6.659, and both are significant at the 5% and 1% levels respectively. The effects are economically large. It clearly provides support for an U-shaped relationship between downstream competition and upstream innovation. That said, with the competition in the downstream industries intensifies, an upstream firm will firstly decrease and then increase her innovation effort. And the U-shaped relationship between downstream competition and upstream innovation still holds when we control for within industry unobservable variables and year fixed effects.

In column (2) of Panel A, we further add firm R&D expenditure, leverage ratio, market-to-book value, return on asset, capital expenditure as firm level controls into the Negative Binomial model specification in column (1). Moreover, following Aghion et al. (2005), we include controls for the impact of horizontal industry competition on upstream firm innovation by adding UP_COMP and UP_COMP_SQUARE into the model specification. We control for year and industry fixed effects as well. The results in column (2) show that the coefficients of downstream competition and its squared term are -7.001 and 5.677, and both are significant at the 10% and 5% levels respectively. It suggests that the U-shaped relationship between downstream competition and upstream innovation still holds after we control for firm characteristics, upstream industry competition, year and industry fixed effects.

Our baseline model is the Negative Binomial model in columns (1) and (2). We also consider alternatives such as Poisson model and OLS in columns (3) – (7). Specifically, in columns (3) and (4), we present the results of the effect of downstream competition on upstream innovation by using Poisson model. As shown in column (3), the coefficients of downstream competition and its square
term are $-3.241$ and $2.680$, and both are significant at the 10% and 5% significant levels respectively. Firm level controls are added into the model specification in column (4). The coefficients of downstream competition and its square term remain significantly negative and positive respectively. These results provide consistent support for an U-shaped relationship between downstream competition and upstream innovation when estimating based on the Poisson model, and controlling for firm characteristics, year and industry fixed effects.

In columns (5) – (7) of Panel A, we estimate the impact of downstream competition on upstream innovation by using OLS method, where the dependent variable becomes the logarithm of one plus citation-weighted patent counts of firms. Column (5) shows the results of the impact of downstream competition on upstream innovation. The coefficients of downstream competition and its squared term are $-3.334$ and $1.983$ respectively. Both are significantly at the 5% level. Columns (6) and (7) add firm characteristics, year fixed effects, and industry fixed effects, which could affect upstream firm innovating activities. The coefficients of downstream competition and its squared term remain negative and positive, and are significant at the 5% and 10% levels respectively.

Overall, the results presented in Panel A provide consistent support for an U-shaped relationship between downstream competition and upstream innovators’ incentives to innovate.

**Differences in the Impact of Competition on Innovation**

To provide additional insights, we conduct a number of tests to examine whether the non-linear U-shaped relationship between downstream competition and upstream innovation changes for upstream firms with different sizes and operating in industries with different innovation intensities. Overall, Panel B of Table 3 shows that the U-shaped relationship between downstream competition and upstream innovation is more pronounced for larger firms than smaller firms and for firms in less innovation intensive industries.

Specifically, columns (1) – (3) of Panel B present the results of how firm size moderates the relationship between downstream competition and upstream firm innovation. To investigate the moderating effect, we include a dummy variable, $SIZE$, into our model specification. $SIZE$ is coded as one if firm size is beyond average; and zero otherwise. In column (1), the coefficients of $SIZE \times DOWN\_COMP$ and $SIZE \times DOWN\_COMP\_SQUARE$ are negative and positive respectively, and both are significant at the 5% level. It indicates that firm size positively moderates the relationship between downstream industry competition and upstream firm innovation. Columns (2) and (3) further control for year and industry fixed effects, and firm level characteristics respectively. The coefficients
of $SIZE \times DOWN\_COMP$ and $SIZE \times DOWN\_COMP\_SQUARE$ remain significantly negative and positive respectively. Overall, the results in columns (1) – (3) provide the support that the U-shaped relationship between downstream competition and upstream innovation becomes more pronounced for larger upstream innovators than for smaller ones. The results on the differences in the impact of competition and innovation resulting from firm size are consistent with, among others, the work from Sanyal and Ghosh (2013), who find that the relative upstream-downstream bargaining power would affect the relationship between downstream competition and upstream innovation. The intuition is that upstream innovators with relatively large size would hold an advantageous bargaining position relative to downstream firms; it then would be more profitable for them to respond to the changes in downstream industry competition by adjusting innovation effort. Therefore, downstream industry competition has a more pronounced U-shaped relationship with upstream innovation when the upstream innovator has larger size.

In columns (4) – (6) of Panel B, we present how the U-shaped relationship between downstream competition and upstream innovation differs for firms in industries with different innovation intensities. To that end, we include a dummy variable, $INNO$, into our model specification. In column (4), the coefficients of $INNO \times DOWN\_COMP$ and $INNO \times DOWN\_COMP\_SQUARE$ are positive and negative respectively, and both are significant at the 5% level. Columns (5) – (6) further control for year and industry fixed effects, and firm characteristics respectively. The coefficients of $INNO \times DOWN\_COMP$ and $INNO \times DOWN\_COMP\_SQUARE$ are significantly positive and negative respectively. In all, the results in columns (4) – (6) suggest that the U-shaped relationship between downstream competition and upstream firm innovation is less pronounced for upstream innovators operating in more innovation intensive industries. The intuition is that compared to firms in less innovation intensive industries, upstream firms operating in innovation intensive industries will have a lower marginal cost of innovation. Given a certain amount of change in marginal benefit of licensing resulting from changes in downstream competition, these firms would be able to respond less to downstream industry competition.

To sum up, consistent with our theory, our empirical results confirm the existence of an U-shaped relationship between downstream competition and upstream innovation. Our estimates also indicate that the U-shaped relationship between downstream competition and upstream innovation becomes more pronounced for firms with large size and firms operating in less innovative industries.

[Insert Table 3 here]
4.1.5 Robustness and Identification

Robustness Considerations

We conduct a rich set of robustness tests and report the main results in Table 4.

First, our main dependent variable, citation-weighted patent counts, is constructed based on weighting firms’ patent counts by their citations. The concern is that patent quality might be sensitive to a specific weighting technique (Aghion, Van Reenee, and Zingales, 2013). To address this concern, we use citations per patent and total citations as alternative proxies for patent quality in the regressions as well. We report the results of the impacts of downstream industry competition on citations per patent and total patent citations in Panel A of Table 4. We apply three different models in our regression: Negative Binomial, OLS, and Poisson models. Columns (1) and (2) present the impact of downstream competition on upstream firm innovation by using citations per patent as a proxy for firm innovation and OLS regression model. In column (1), the coefficients of downstream competition and its squared term are \(-1.917\) and \(1.384\) respectively, and both are significant at the 5% significance level. The results in column (2) show that the coefficients of downstream competition and its squared term remain negative and positive respectively when controlling for firm characteristics, year fixed effects, and industry fixed effects. Column (3) presents the estimation results from Poisson regression model, and the U-shaped relationship between downstream competition and upstream innovation still holds. Columns (4) – (6) show the impact of downstream competition on upstream innovation by using total patent citations as a proxy for firm innovation. Overall, the results in columns (4) – (6) provide support for an U-shaped relationship between downstream competition and upstream firm innovation.

Second, we re-run our regressions by using sample period 1976 - 2001 to address the concern that patent citations close to the end of sample year would be biased. Though NBER updates the data until 2006, some patents applied for after 2001 may not have been granted due to significant grant lags in some technology areas. Furthermore, most patents require a significant number of years to reach their full citation potential. By allowing five years from the date of application, we attempt to minimize these problems. We report the results in Panel B of Table 4. In Columns (1) – (3), the coefficients of downstream competition on upstream firm innovation are highly significant based on OLS method. And columns (4) – (6) present the results based on Negative Binomial model and Poisson model respectively. Just like the baseline model, the U-shaped relationship between downstream competition and upstream innovation is highly significant.
Third, our finding of an U-shaped relationship between downstream competition and upstream innovation differs from the work of Aghion et al. (2005), which finds an inverted-U relationship between horizontal industry competition and innovation. The concern is that this difference may be driven by different industries in the samples of these two studies. To address this concern, we re-run our regressions using the same sample industries covered by Aghion et al. (2005), i.e. four-digit SIC from 2000 to 3999, and report the results in Panel C of Table 4. Specifically, columns (1) – (3) present the results based on OLS estimation method. The coefficients of downstream competition and its square term are negative and positive respectively, and both are significant when controlling for firm level characteristics, year fixed effects, and industry fixed effects. Columns (4) - (6) report the results from Negative Binomial model and Poisson model respectively. Overall, the results in Panel C of Table 4 provide support that downstream competition has an U-shaped relationship with upstream innovation.

Fourth, we use an alternative, Text-based Network Industry Classifications (TNIC), to capture downstream industry competition. Hoberg and Philips (2010, 2016) develop TNIC by computing firm pairwise similarity scores from text analysis in the firm 10-K product descriptions. The product similarities based TNIC provides a good fit to our theoretical model, where firms compete with differentiated products (or locations). Therefore, we go further to check whether our main results hold when using TNIC-based industry competition. Specifically, instead of using TNIC3HHI (provided by Hoberg and Philips (2010, 2016)), an industry concentration measure calculated based on TNIC, we compute the TNIC-based Lerner index to capture the downstream industry competition. The reason is that Lerner index is considered to be a better measure for industry competition (Aghion et al., 2005), and it can also keep consistent with our abovementioned baseline model. We apply a Negative Binomial model to do the analysis, controlling for firm leverage, market-to-book ratio, return to asset, capital expenditure, and year fixed effects, which may affect firms’ innovative activities. The standard errors in our regressions are clustered at the five-digit NAICS level. Panel D of Table 4 presents the results. As shown in columns (1) – (3), all the coefficient estimates on TNIC-based downstream industry competition, $DOWN\_COMP\_TNIC$, are negative and significant at the 1% or 5% level. And all the coefficient estimates on the square term of TNIC-based downstream competition, $DOWN\_COMP\_TNIC^2$, are positive and significant at the 1% or 5% level. This suggests that an U-shaped relationship between downstream competition and upstream innovation still holds when using the TNIC-based industry competition measure.
Finally, to address the concern that a significant coefficient on the square term of downstream competition is necessary but not sufficient to establish a quadratic U-shaped relationship (Hanns, Pieters, and He, 2016), we go through the following checks: (1) we check whether the threshold point is within our data range. As we have checked, the range of our independent variable, downstream industry competition, is from 0.42 to 0.88, and all the threshold points are within our data range. Taking column (2) in Table 3 in our baseline model as an example, the turning point of the U-shaped relationship is $0.6165(7.001/(2 \times 5.677) = 0.6165$), which is clearly within our data range. (2) We also split our data sample into different percentiles to see how the relationship between downstream competition and upstream innovation varies with the subsamples. We first run simple regressions of upstream innovation on downstream competition using the 10th, 15th, 20th, 25th, 30th, and 40th percentiles of our data respectively, each of them gives us a negative and significant relationship between downstream competition and upstream innovation. Next, we use the 90th, 85th, 80th, 75th, 70th, and 60th percentiles of our sample to run the regression respectively, finding that downstream competition is positively related to upstream innovation with all of these subsamples. Taken together, the above results based on sample splitting provide support for the U-shaped relationship existing between downstream competition and upstream innovation. Moreover, we add firm level characteristics into the regressions, and control for year fixed effects and industry fixed effects as well, the results based on some subsamples become insignificant, but the results based on 10th and 90th percentiles of our data keep the expected signs and significant. (3) Finally, we add a cubic term of downstream industry competition into our model specification to test if the nonlinear relationship is S-shaped rather than U-shaped. We find out that the coefficient estimates on downstream competition become insignificant with the cubic term added in the model, and the model goodness of fit has only been improved by 0.0002. Thus, it is unlikely that downstream competition has a S-shaped relationship with upstream innovation. The model with a quadratic term works better for our data. The relevant regression results of these checks are suppressed for brevity.

To sum up, all the above results point into the direction of an U-shaped relationship between downstream competition and upstream innovation.

[Insert Table 4 here]

**Identification Strategy**

The results so far show that downstream industry competition has an U-shaped impact on upstream firm innovation. In other words, when downstream competition is at a lower level, upstream firm
innovation would decrease in downstream competition; whereas as the downstream competition further intensifies, upstream firm innovation would increase in downstream competition. A potential concern, however, relates to the endogeneity of downstream industry competition. Upstream firm innovation could affect the intensity of competition in the downstream product market. For instance, more upstream firm innovation would result in more technologies available to downstream firms and which in turn would affect their competitive action. Moreover, some omitted variables correlated to both upstream innovation and downstream competition would bias our results as well. As such, downstream industry structure and upstream firm innovation may be jointly determined. We address this problem in this subsection.

The quasi-natural experiment: reductions of import tariff rates To address the potential endogeneity of downstream industry competition, we examine the response of upstream firm innovation to unexpected variations of downstream industry import tariff rates in a quasi-natural experiment setting. With the globalization of the economic activities and trade openness, domestic firms are increasingly exposed to the competition from foreign rivals (Bernard, Jensen, and Schott, 2006). Reductions of import tariff rates significantly decrease the cost for foreign firms to enter U.S. product markets and therefore increase the presence of goods and services from foreign rivals. This penetrations of imports spurs an increase in the competitive pressure that domestic firms face in product markets.

We follow Fresard (2010) and Valta (2012) to use large reductions of import tariff rates as events that trigger a sudden increase in the competitive pressure faced by domestic firms. We gather U.S. import date compiled by Schott (2010) for the sample period 1989 – 2005. For each industry-year, we compute the ad valorem tariff rate as the duties collected at U.S. Customs divided by the Free-On-Board custom value of imports. Next, we characterize “competitive shocks” as large variations in the tariff rate in terms of the deviation of the yearly change in tariff rates from the same industry’s median or average change. To do so, we first compute for each industry the median (or average) tariff rate change as well as the largest tariff rates changes. Then we define for each downstream industry the dummy variable, \( SHOCK_{k,t} \), which equals one if the largest tariff rate reduction in downstream industry \( k \) by time \( t \) is larger than three times the median tariff rate reduction in that industry; and zero otherwise\(^{23}\). Finally, based on the upstream-downstream industry relationships

\(^{23}\)We also try two alternatives in section 4.1.5, defining the competitive shock by whether the largest tariff rate reduction is larger than two times (or one and a half) the median tariff rate reduction. And our results are robust to different definitions of competitive shock.
we identified in section 4.1.2, for an upstream industry $j$, we take the average of competitive shocks coming from the downstream industries related to the upstream industry $j$. We then get the average downstream industry competition for the upstream industry $j$ in year $t$, $SHOCK_{j,t} = \frac{\sum_k SHOCK_{k,t}}{n_{j,t}}$, where $SHOCK_{k,t}$ is the import tariff rate reduction that the downstream industry, $k$, experiences by year $t$; and $n_{j,t}$ is the number of downstream industries related to the upstream industry $j$ in year $t$; $SHOCK_{j,t}$ is the average of the import tariff rate reductions in all the downstream industries related to the upstream industry $j$ in year $t$.

**Empirical method** To investigate the effect of large shifts of import tariff rates on firm innovation, we estimate the following model:

$$CITE\_WEIGHT\_PAT_{i,j,t} = \beta_0 + \beta_1 \cdot SHOCK_{j,t} + \beta_2 \cdot SHOCK^2_{j,t} + \gamma \cdot Z_{i,t} + \delta_t + \alpha_j + \varepsilon_{i,j,t}. \quad (18)$$

As in model (18), subscript $i$, $j$ and $t$ represent the firm, upstream industry, and year respectively. The dependent variable $CITE\_WEIGHT\_PAT_{i,j,t}$ is the citation-weighted patent counts that firm $i$ has in year $t$. The variable $SHOCK_{j,t}$ is the average import tariff reduction of all the downstream industries related to an upstream industry $j$ that firm $i$ belongs to in year $t$. We also include upstream industry fixed effects, $\alpha_j$, and year fixed effects, $\delta_t$, in the estimations. The industry fixed effects are necessary to identify the within-industry change in innovation when competition intensifies, keeping everything else constant. The estimate of the competitive shock’s effect are $\beta_1$ and $\beta_2$, the coefficients of $SHOCK_{j,t}$ and $SHOCK^2_{j,t}$. This approach allows comparing the change in firm innovation in industries that do experience a competitive shock to the change in firm innovation in industries that do not experience a competitive shock.

Choosing import tariff rate reductions as an exogenous competitive shock is based on the following considerations: First, import tariff rate reductions can provide us with sufficient time series and cross-country variations to identify the effect of competitive shocks in downstream industries on upstream firm innovation. Second, import tariff rate reductions can bring relevant real-side changes to the competitive nature of product markets. Third, the source of variation in import tariff rate that shifts the downstream competitive environment is exogenous to upstream firm innovation and partly unanticipated by firms. All of these can ensure a proper identification of the causal effect of tariff rate reductions on upstream firm innovation.
**Tariff rate reductions and upstream firm innovation** Table 5 presents the estimation results from model (18). In the benchmark case, we define a shock in a downstream industry within a year if the import tariff rate reduction is at least three times larger than the median tariff rate reduction in that industry in that year.

In column (1), we examine the impact of downstream competition on upstream innovation by using import tariff rate reductions as an exogenous competitive shock. We also control for year fixed effects and industry fixed effects in the estimation. As shown in column (1), the coefficient of $SHOCK$ has a value of 0.467, and is negative and significant at the 5% level. The coefficient of $SHOCK\_SQUARE$ has a value of 0.556, and is positive and significant at the 1% level. It suggests that downstream competition has an U-shaped relationship with upstream innovation when we use the exogenous competitive shock to address the potential endogeneity concern of industry competition.

In column (2), we add $RDTX, LEV, MB, ROA, CAPXTA$ to control for firm characteristics that may affect firm innovation activity. We also control for year and industry fixed effects. The coefficients of $SHOCK$ and $SHOCK\_SQUARE$ remain negative and positive respectively, and both are significant at the 1% significance level. It provides support for an U-shaped relationship existing between downstream competition and upstream innovation when controlling for firm characteristics, year fixed effects, and industry fixed effects.

In columns (3) and (4), we modify the way we define $SHOCK$. In addition to the definition of a competitive shock in the benchmark case in columns (1) - (2), we now define $SHOCK_{k,t}$ in another two different ways. Specifically, in column (3), we set the competitive shock, $SHOCK_{k,t}$, equals one if the import tariff rate reduction in a downstream industry $k$ is two times larger than the median tariff rate reduction in that industry by year $t$. In column (4), $SHOCK_{k,t}$, equals one if the tariff rate reduction is one and a half times larger than the average tariff rate reduction in that industry. In both columns, the coefficients of $SHOCK$ and $SHOCK\_SQUARE$ keep significantly negative and positive respectively, suggesting our results are robust to different definitions of competitive shock.

Overall, the results in Table 5 substantiate the main finding that downstream competitive shock has a causal U-shaped relationship with upstream firm innovation in a quasi-natural experimental setting.

[Insert Table 5 here]
4.2 Downstream Competition and Licensing Strategy

4.2.1 Economic Mechanism: Licensing Strategy

Our current results are consistent with our theoretical model implications that downstream industry competition has an U-shaped impact on upstream firm innovation. In other words, when there is a low level of competition in the downstream product market, competition is negatively related to upstream innovation; while this relationship becomes positive as downstream competition intensifies. In this section, we explore the plausible underlying economic mechanism through which this U-shaped relationship occurs. In the spirit of our theoretical model, the mechanism we investigate is the channel of upstream firms’ licensing strategies.

As implied by our foregoing theoretical model, when downstream competition is at a lower level, upstream firm would prefer marketed-wide licensing strategy to targeted licensing due to a higher licensing revenue associated with the former strategy. Moreover, when the market-wide licensing strategy is chosen, upstream firm’s incentive to innovate is decreasing in downstream competition, for the reason that rent reduction effect dominates business stealing effect. Conversely, targeted licensing strategy becomes optimal for the upstream firm when downstream competition is at a higher level; and firm innovation is increasing in downstream competition under targeted licensing. Taken together, it is therefore expected that upstream innovation is initially decreasing in downstream competition under market-wide licensing, and then increasing in it under targeted licensing strategy. In other words, with downstream industry competition intensifies, upstream firms would more likely to choose targeted licensing strategy rather than market-wide licensing.

4.2.2 Data Sample

To investigate these conjectures, we examine how upstream licensing strategies play a role in the relationship between downstream competition and upstream innovation. Specifically, as described in the subsection of data sample, we collect licensing deal data from the Strategic Alliance database of Securities Data Company (SDC). The SDC database records all publicly announced alliance deals worldwide and provides detailed information about licensing deals, such as licensing contract type (i.e. exclusive, non-exclusive, cross licensing), the identities of licensors and licensees, the SIC codes of the participants and alliances, and so forth. Despite some limitations to SDC database, the information on licensing contract type, which is one of the main variables we will use in our model, is actually
quite accurate (Anand and Khanna, 2000). Due to that SDC focuses more on US firms, and the deal sample prior to 1990 is incomplete, we restrict our analysis to the licensing deals between two public US firms from 1990 – 2006. By reading through the texts which describe the details about licensing deals, we are able to distinguish licensors and licensees, and determine whether the participants are licensing technology or not. We are also able to eliminate the agreements for which the agreements are about termination of previous agreements or litigation between participants, or less than two participants are involved. From SDC, we come out with an initial set of 5,908 licensing deals announced from January 1, 1990 to December 31, 2006, corresponding to 6,870 companies traded in the United States. Furthermore, we collect data on publicly traded companies in the United States extracted from Compustat database. In particular, we obtain data on firm level and industry level characteristics, such as industry concentration, industry growth rate, firm size, etc. We therefore need to drop firms where key variables are missing for our analysis. Merging with the abovementioned SDC dataset, we have, thus, reached a sample with 1,415 firm-year observations. Our final step of data collection is to link the merged dataset with NBER Patent Citation Dataset, obtaining firms’ information on patenting since January 1, 1990. This gives us a final sample with 605 observations, with 631 licensors and licensees traded in United States.

4.2.3 Empirical Results

Due to the dependent variables in our subsequent analysis are discrete and nonnegative, we employ a Negative Binomial model to investigate how licensing strategy affects the relationship between downstream competition and upstream innovation. Panel A of Table 6 presents the results that examine that impact of downstream competition and licensing strategy on upstream innovation. The dependent variable, CITE_WEIGHT_PAT, is the citation-weighted patent counts for firms, a proxy for upstream firm innovation. The independent variables are DOWN_COMP, measuring downstream industry competition; LICENSE_TARGETED, a dummy setting to 1 if targeted licensing is used, and zero otherwise; and DOWN_COMP* LICENSE_TARGETED, an interaction of downstream competition and targeted licensing. We include a vector of firm level characteristics that may impact a firm’s future innovation productivity. We also include year fixed effects to control for the impact of some variables that change over time. Anand and Khanna (2000) suggest that the structure and type of licensing contracts show robust cross-industries differences. Therefore, we cluster the standard errors by four-digit SIC industry level. As shown in column (1), the coefficient estimate on DOWN_COMP
is negative with a value of 8.114, and significant at the 1% level, suggesting that downstream industry competition has a negative impact on upstream firm innovation. Moreover, the coefficient estimate on $DOWN\_COMP*LICENSE\_TARGETED$ is positive with a value of 11.514, and significant at the 1% level. Thus, with the presence of targeted licensing strategy, the net impact of downstream industry competition on upstream firm innovation would be positive with a value of 3.4 ($11.514 - 8.114 = 3.4$). This suggests that with an initially low level of downstream industry competition, upstream firm innovation is decreasing in downstream competition; when downstream industry competition intensifies, upstream innovators adopt more targeted licensing strategies relative to market-wide licensing; and the net impact of downstream competition on upstream innovation becomes positive under targeted licensing. Taken together, it clearly provides evidence of an U-shaped relationship between downstream competition and upstream innovation. We add firm level characteristics and year fixed effects in Columns (2) and (3) respectively, and the results suggest a similar direction of the abovementioned impacts.

Additionally, Panel B of Table 6 presents the results that directly examine the impact of downstream competition on upstream firms' decision on licensing strategy. Specifically, we look at how the propensity to apply a targeted licensing strategy is determined by the product market competition level in the downstream industries. We include firm level and industry level characteristics which might have impacts on the choice of licensing strategies. In particular, drawing from Anand and Khanna (2000), Kim and Vonortas (2006), Somaya, Kim, and Vonortas (2010), we include four firm level controls: Firm Size, Prior License (a proxy for whether a focal firm issues licenses before or not), Knowledge Stock, and Complexity (a proxy for the complexity of technology); and three industry level controls: Industry Concentration, Industry Growth, and IPR Strength. We also include year fixed year, and cluster the standard errors at 4-digit SIC industry level. Given that our dependent variable is count data, we choose to use negative binomial model as shown in Column (1). We also try Poisson model and OLS in Columns (2) and (3) respectively. As shown in Columns (1) – (3), all the coefficient estimates on downstream industry competition, $DOWN\_COMP$, are positive and significant at the 1% (or 5%) level. It suggests that with an intensified downstream industry competition, an upstream innovator would more likely to adopt a targeted licensing strategy; she may in fact switch from a market-wide licensing to targeted licensing. This finding keeps robust and significant after controlling a vector of firm and industry level characteristics and year fixe
Overall, our findings in this section suggest that upstream licensing strategy appears to be the underlying economic mechanisms through which downstream competition has an U-shaped effect on upstream innovators’ incentives to innovate. Specifically, when downstream competition is at a low level, upstream innovators are more likely to choose market-wide licensing, and the innovators’ incentive to innovation is decreasing in downstream competition; while as downstream competition intensifies, targeted licensing strategy becomes optimal, and upstream firm innovation is increasing in downstream competition.

5 Concluding Remarks

Given that much of the innovation taking place in practice is not done in-house, but instead is traded in large and growing technology markets. In this paper, we present a model which places technology markets at the centre of an analysis of downstream competition and upstream innovation. Specifically, we consider an upstream innovator and two downstream competitors; and examine the impact of competition on the innovator’s innovation strategy under targeted licensing, when she can license her innovation to one of the downstream competitors; and under market-wide licensing, when she licenses to both. We show that in equilibrium a threshold level of competition may exist such that below that threshold, market-wide licensing is optimal and innovation is decreasing in competition; while above the threshold, targeted licensing is optimal and innovation is increasing in competition.

This non-monotonic relationship between competition and innovation emerging from our model yields three key empirical implications. First, it predicts that downstream competition increases the appeal of targeted licensing relative to market-wide licensing for the innovator; and that she may switch from market-wide to targeted licensing as competition intensifies. Second, our model suggests that downstream competition increases innovation incentives for upstream innovators who choose a targeted licensing strategy, but decreases innovation incentives for innovators choosing a market-wide strategy. Third, and more general, our model points out that the relationship between product market competition and innovation is subtle and may be increasing, decreasing, or U-shaped, depending on the exogenous relative cost of market-wide versus targeted licensing.

Using U.S. data from 1976—2006 across all industries, we firstly empirically investigate the impact of downstream industry competition on upstream innovators’ incentives to innovate. The evidence from U.S. data provides consistent support for an U-shaped relationship between downstream com-
petition and upstream innovation, i.e. there is a threshold level of competition such that below that threshold, upstream innovation is decreasing in downstream competition; while above the threshold, upstream innovation is increasing in downstream competition. Moreover, this U-shaped relationship becomes more pronounced for larger firms than smaller firms and for firms operating in industries with less innovation intensity. Further our understanding of this U-shaped relationship is to examine the causal impact of competition on upstream innovation in a quasi-natural experiment setup. To that end, we use import tariff rate reductions as an exogenous competitive shock to address the potential endogeneity concerns. Our identification test suggests that downstream competition has a causal U-shaped relationship with upstream innovation. Finally, data on licensing deals from SDC database provides empirical support that upstream innovators’ licensing strategy is the underlying economic mechanism. In particular, as downstream competition intensifies, targeted licensing strategy becomes more appealing to upstream innovators than market-wide licensing; and under targeted (market-wide) licensing, upstream innovation is increasing (decreasing) in downstream competition.

In order to provide clear, stark and tractable results, we made some strong assumptions and presented a highly stylized model. One question that naturally arises concerns the optimality of the licensing contract. While much of the licensing literature discussed in the introduction debates the circumstances under which fixed fees, auctions, royalties, or two-part tariffs might be optimal, in this paper we abstract from this debate and motivate assumptions about contractual incompleteness and transaction costs in order to ensure the (de facto) optimality of the simplest of licensing contracts: the fixed fee. In Section 7, we discuss what would happen in the context of an auction and show that the results are very similar to those of the main model. As discussed by Kamien (1992) and others, models with optimal two-part tariffs are analytically more complicated, and beyond the scope of this paper where our focus is on the effects of competition on upstream innovation, rather than on the specific contractual terms under which this innovation is transferred in technology markets.

Another question that arises concerns the robustness of our results to demand specifications other than Hotelling. Competition affects our models in two ways - by affecting equilibrium levels of innovation, and licensing payoffs to the innovator. As discussed in the paper, targeted licensing allows one firm to gain a cost advantage over its rival, yielding strong demand and large markups, which in turn amplify the positive effects of competition. In contrast, market-wide licensing allows firms to not fall behind their competitor; if they did they would have low demands and thin markups. In this market-wide context, the positive effects of competition are muted by these low demands and
markups. We believe that these intuitions are quite general and conjecture that qualitatively similar results would obtain in other address models (e.g. Salop, 1979), as well as in logit models and in CES models à la Dixit-Stiglitz (1977). Modeling the impact of competition in a richer model of optimal license contracting, or under the demand specifications just enumerated, are natural and appealing extensions of this model, and which we look forward to examining in future research.

6 Appendix A - Proofs

6.1 Proof of Lemma 1

Using (24), we can express (27) as follows:

\[ -2 \left[ -\frac{1}{3} \left( \frac{1}{2} - \frac{\Delta^*_M \theta}{6} \right) + \frac{\theta}{6} \left( \frac{1}{\theta} - \frac{\Delta^*_M \theta}{3} \right) \right] = \Delta^*_M; \text{ or} \]

\[ \frac{2}{3} - \frac{2 \Delta^*_M \theta}{9} = \Delta^*_M; \]

which yields \( \Delta^*_M = 6/(9 + 2\theta) \).

Note that our parametric restriction \( \theta \in \Theta \) with \( \Theta = (0, 9/2) \) ensures that the second-order condition, \( \frac{2\theta}{9} < 1 \), is satisfied. Note also that at \( \Delta^*_M \), the smallest expected demand and price-cost margin a Firm \( i \) can expect to obtain (in the no-access case) simplify to \( d_i = \frac{1}{2} - \Delta^*_M \theta = \frac{1}{2} \) and \( P_i = \frac{1}{\theta} - \frac{\Delta^*_M \theta}{3} = \frac{1}{\theta} - \frac{2}{(9 + 2\theta)} \), respectively; which are both strictly positive for all \( \theta \in \Theta \).

Using (24) and substituting \( \Delta^*_M = 6/(9 + 2\theta) \) into expressions (31) and (32), we obtain \( z_{1M} = \frac{2(9 + \theta)}{(9 + 2\theta)^2} \) and \( Z^*_M = \frac{2}{(9 + 2\theta)} - h \), respectively. \( \square \)

6.2 Proof of Lemma 2

Using (24), we can express (10) as follows:

\[ \frac{1}{3} \left( \frac{1}{2} + \frac{\Delta^*_T \theta}{6} \right) + \frac{\theta}{6} \left( \frac{1}{\theta} + \frac{\Delta^*_T \theta}{3} \right) = \Delta^*_T; \text{ or} \]

\[ \frac{1}{3} + \frac{\Delta^*_T \theta}{9} = \Delta^*_T; \]

which yields \( \Delta^*_T = 3/(9 - \theta) \).

Note that our parametric restriction \( \theta \in \Theta \) with \( \Theta = (0, 9/2) \) ensures that the second-order condition, \( \frac{\theta}{9} < 1 \), is satisfied. Note also that at \( \Delta^*_T \), the smallest expected demand and price-cost margin a Firm \( i \) can expect to obtain (in the no-access case) simplify to \( d_i = \frac{1}{2} - \Delta^*_T \theta = \frac{1}{2} \) and \( P_i = \frac{1}{\theta} - \frac{\Delta^*_T \theta}{3} = \frac{1}{\theta} - \frac{1}{(9 - \theta)} \), respectively; which are both strictly positive for all \( \theta \in \Theta \).
Using (24) and substituting $\Delta_T^* = 3/(9 - \theta)$ into expressions (8) and (9), we obtain $z_{1T}^* = \frac{18 - \theta}{2(9 - \theta)}$, and $Z_T^* = \frac{1}{18 - 2\theta}$, respectively. □

6.3 Proof of Proposition 2

Recall from Lemmas 1 and 2 that $Z_M^* = \frac{2}{(9 + 2\theta)} - h$ and $Z_T^* = \frac{1}{18 - 2\theta}$. It then follows that $\lim_{\theta \to 0} Z_T^* - Z_M^* = -1/6 + h$ and that $\lim_{\theta \to 9/2} Z_T^* - Z_M^* = h$, and together with Proposition 1, this implies that:

- If $h \in (0, 1/6)$ - there exists a threshold level of competition $\theta^*(h) \in \Theta$ such that the innovator chooses market-wide licensing for all $\theta \in (0, \theta^*(h))$, and chooses targeted licensing for all $\theta \in [\theta^*, 9/2)$.

- If $h$ is high - $h \geq 1/6$ - targeted licensing is the optimal choice for the innovator for all $\theta \in \Theta$.

- If $h$ negative - $h \leq 0$ - targeted licensing is the optimal choice for the innovator for all $\theta \in \Theta$.

To see that $\partial \theta^*(h)/\partial h < 0$, note that $\theta^*(h)$ is the value of $\theta$ such that $Z_T^* - Z_M^* = 0$, or $A = \frac{1}{18 - 2\theta^*} - \frac{2}{(9 + 2\theta^*)} + h = 0$. The implicit function theorem then yields $\frac{\partial \theta^*}{\partial h} = -\frac{\partial A/\partial h}{\partial A/\partial \theta^*} < 0$. □

7 Appendix B - Further Theoretical Considerations

7.1 Revisiting the Tradeoff Between Market-Wide and Targeted Licensing

In the main analysis we have shown that competition increases the appeal of targeted licensing relative to market-wide licensing, and hence that as competition intensifies, the innovator may switch from the latter to the former. In this section, we explore further the licensing tradeoff and how it is affected by competition.

At date 0, the innovator decides which type of licensing to opt for. She chooses market-wide licensing over targeted licensing iff $Z_M^* \geq Z_T^*$, iff:

$$\sum_{i=1}^{2} z_{iM}(\Delta_M, \theta) - K_M(\Delta_M) > z_{1T}(\Delta_T, \theta) - K_T(\Delta_T).$$

Re-writing expression (19) in the following way helps highlight the three key factors affecting the tradeoff between market-wide licensing and targeted licensing:

\footnote{Since innovation levels and license fees are identical for firms 1 and 2, we express the licensor’s payoff as twice the payoff from firm 1 for simplicity.}
\[ [z_{2M} (\Delta_M, \theta)] \\
- [(z_{1T} (\Delta_M, \theta) - K_T (\Delta_M)) - z_{1M} (\Delta_M, \theta) - K_M (\Delta_M)] \\
- [(z_{1T} (\Delta_T, \theta) - K_T (\Delta_T)) - (z_{1T} (\Delta_M, \theta) - K_T (\Delta_M))] > 0. \]

The first square-bracketed factor captures the revenue advantage of market-wide licensing, i.e. the extra revenue obtained from licensing to the second firm in the downstream market.

The second square-bracketed factor captures the dissipation disadvantage of market-wide licensing. For a given innovation \( \Delta_M \) (produced at cost \( K_T (\Delta_M) \) under targeted licensing and at cost \( K_M (\Delta_M) \) under market-wide licensing) licensed to downstream Firm 1, the no-access profits for Firm 1 under market-wide licensing is smaller than the access profits for that firm under targeted licensing; because as discussed above Firm 1 is at a cost disadvantage in the former case and at a cost advantage in the latter case. Accordingly, for a given innovation \( \Delta_M \), the license fee extracted under market-wide licensing is lower than the license fee extracted under targeted licensing.

Finally, the third square-bracketed factor captures the innovation disadvantage of market-wide licensing. It represents the part of the difference between the two types of licensing that comes from different innovation investments being made. As highlighted in Lemmas 1 and 2 equilibrium innovation could be greater or lower under market-wide licensing than under targeted licensing, and hence this disadvantage could be positive or negative.

As shown in Section 3.1, competition reduces the revenue advantage of market-wide licensing and increases its dissipation disadvantage.\(^{25}\) Moreover, we know from Proposition 3 that competition increases \( \Delta_T \) and reduces \( \Delta_M \); thus competition increases the innovation disadvantage. This is another way to express the positive impact of competition on the appeal of targeted licensing relative to market-wide licensing stated in Proposition 1.

The revenue advantage and the dissipation disadvantage of market-wide licensing are closely related to the revenue effect and rent dissipation effect, respectively, identified in Arora and Fosfuri’s (2003) insider-patentee paper. In their model, each incumbent competes in a differentiated downstream product market where, similar to our model competition is captured by the degree of substitutability between products. Each incumbent decides how many licenses to issue to potential new entrants, anticipating that the licensee will enter the market with a product identical to that of the incum-

\(^{25}\)The discussion of Proposition 1 in Section 3.1 yields two points of relevance here: 1) the innovator’s payoff from market-wide licensing decreases with competition; and 2) the innovator’s payoff from targeted licensing increases with competition. Point 1) implies that the revenue advantage decreases with competition. Points 1) and 2) together imply that the dissipation disadvantage increases with competition.
bent licensor. Issuing one more license generates additional revenue (revenue effect), but reduces the incumbent’s profits (rent dissipation effect)\(^\text{26}\) by adding a direct competitor in the downstream market.

Despite highlighting two similar factors in the licensing tradeoff, Arora and Fosfuri’s (2003) model differs from ours along critical dimensions. First, while as in our model competition reduces the revenue effect; in contrast to our model it also reduces the rent dissipation effect, because the negative impact of the licensee’s market entry is now spread more easily across all incumbents. In their model, the second effect dominates, and hence competition leads to more licensing, not less. Second, unlike our model of endogenous innovation, their setup considers firms’ licensing strategy for a given, exogenously determined innovation level. This exogeneity precludes any analysis of the innovation disadvantage of market-wide licensing discussed above, or of the central research question of this paper, namely the subtle connection between competition, licensing, and innovation.

7.2 Auction Contract

In the main model we assume that transaction costs associated with auctions are prohibitively high, making them difficult to implement. In this section we relax this assumption and discuss the results of our model in the context of an auction setup, and show that similar results can be obtained.

Consider the case of targeted licensing, and suppose that the innovator auctions one license. For a given innovation \(\Delta_{Ta}\) to be licensed to the winner of the auction, the equilibrium auction bid by Firm \(i\) is very similar to - though distinct from - the equilibrium license fee in the main model:\(^\text{27}\)

\[
zh(Ta, 0, \theta) = \pi_i (\Delta_{Ta}, 0, \theta) - \pi_i (0, \Delta_{Ta}, \theta).
\]

The only difference is that in the main model the innovator commits to sell on Firm 1 only, and hence Firm 1’s no-access profit (i.e. if it does not get the innovation) is \(\pi_1 (0, 0, \theta)\); while here each downstream firm conjectures that if it does not get the innovation the rival firm will get it, and hence the no-access profit for Firm \(i\) is \(\pi_i (0, \Delta_{Ta}, \theta)\). Using \(zh(Ta, 0, \theta)\) and expression (24), one can readily show that: Under targeted licensing in an auction setup, a unique equilibrium exists, in which the innovator chooses innovation levels \(\Delta_{Ta} = 2/3\). This in turn implies - assuming Firm 1 wins the auction - downstream price-cost margins \(P_1 (\Delta_{Ta}, 0, \theta) = \left[\frac{1}{2} + \frac{3}{5}\right]\) and \(P_2 (0, \Delta_{Ta}, \theta) = \left[\frac{1}{2} - \frac{2}{5}\right]\); and expected demands \(d_1 (\Delta_{Ta}, 0, \theta) = \left[\frac{1}{2} + \frac{\theta}{5}\right]\) and \(d_2 (0, \Delta_{Ta}, \theta) = \left[\frac{1}{2} - \frac{\theta}{5}\right]\). Equilibrium auction bid, and payoff to the innovator, simplify to \(zh(Ta) = 4/9\), and \(zh(Ta) = 2/9\), respectively.

\(^{26}\)The dissipation effect also plays a key role in Arora et al.’s (2012) recent work on the tradeoff between decentralized licensing - where the business unit has authority over licensing decisions - and centralized licensing in a specialized licensing unit. As well, see related work by Fosfuri (2006).

\(^{27}\)We add subscript \(a\) to remind the reader that we are examining the auction case.
Under market-wide licensing, auctioning two licenses to the two downstream firms yields the trivial result that both firms would bid the reservation price set by the innovator, and hence the problem reverts to the problem examined above. For a given innovations $\Delta_{Ma}$ to be licensed to downstream firms $i$ and $j$, the equilibrium price received by the innovator is exactly the same as the optimal license fee charged to Firm $i$ in the main model: $z_{iMa}(\Delta_{Ma}, \Delta_{Ma}, \theta) = \pi_i(\Delta_{Ma}, \Delta_{Ma}, \theta) - \pi_i(0, \Delta_{Ma}, \theta)$. Thus under market-wide licensing the outcome is identical to the outcome in the main model, which is stated in Lemma 1, and which we repeat here for convenience. Under market-wide licensing, a unique equilibrium exists, in which the innovator chooses innovation levels $\Delta_{Ma}^* = \Delta_{M}^* = \frac{6}{9+2\theta}$. This in turn implies downstream price-cost margins $P_1(\Delta_{Ma}^*, \Delta_{Ma}^*, \theta) = P_2(\Delta_{Ma}^*, \Delta_{Ma}^*, \theta) = 1/\theta$; and expected demands $d_1(\Delta_{Ma}^*, \Delta_{Ma}^*, \theta) = d_2(\Delta_{Ma}^*, \Delta_{Ma}^*, \theta) = 1/2$. License fees, and payoff to the innovator, simplify to $z_{1Ma}^* = z_{2Ma}^* = \frac{2(9+\theta)}{(9+2\theta)^2}$, and $Z_{Ma}^* = \frac{2}{(9+2\theta)} - h$, respectively.

One can see that while equilibrium innovation and innovator payoff are now independent of competition under targeted licensing in the auction case, the key results are still similar to those of the main model. In particular, competition continues to increase the appeal of targeted licensing over market-wide licensing ($\partial (Z_{Ta}^* - Z_{Ma}^*)/\partial \theta > 0$). Overall, from the foregoing analysis one can derive results equivalent to Proposition 4 in the context of an auction. In an auction setup, if the exogenous (relative) cost of market-wide licensing $h$ is moderately negative - $h \in (-1/9, 0)$ - there exists a threshold level of competition $\theta_a^*(h) \in \Theta$ such that the innovator chooses market-wide licensing for all $\theta \in (0, \theta_a^*(h))$, and chooses targeted licensing for all $\theta \in [\theta_a^*, 9/2)$. If $h$ is positive - $h \geq 0$ - targeted licensing is the optimal choice for the innovator for all $\theta \in \Theta$. And if $h$ very negative - $h \leq -1/9$ - market-wide licensing is the optimal choice for the innovator for all $\theta \in \Theta$.

### 7.3 Licensing Contract With A Fixed Fee Plus Royalty

In the main model we assume that the licensing contract is based on fixed fee. In this section we relax this assumption and discuss the results of our model in the context of the licensing contract based on both royalty and fixed fee.

**Targeted Licensing.** Suppose that the innovator plans to license her innovation to Firm 1 only. In addition of charging a fixed licensing fee, the innovator imposes royalties in the licensing deal as well. We derive the equilibrium by backward induction.

At date 3, price competition takes place between firms 1 and 2. Two firms choose prices to maximize their expected payoff, taking costs and innovations as given:
\[
\max_{p_1} \pi_1 (\Delta_T, p_1, p_2, \theta, r) = \max_{p_1} (p_1 - c + \Delta_T - r) d_1 (p_1, p_2, \theta), \tag{21}
\]

\[
\max_{p_2} \pi_2 (p_2, p_1, \theta) = \max_{p_2} (p_2 - c) d_2 (p_1, p_2, \theta), \tag{22}
\]

where \(r\) is the per unit royalty, and the expected demand \(d_1 (p_1, p_2, \theta)\) and \(d_2 (p_1, p_2, \theta)\) are defined as in (1). Taking the first-order conditions (FOCs) with respect to price, and solving the resulting system of two equations yields the following equilibrium profits:

\[
\pi_1 (\Delta_T, \theta, r) = \left[ \frac{1}{\theta} + \frac{\Delta_T - r}{3} \right] \left[ \frac{1}{2} + \frac{(\Delta_T - r)\theta}{6} \right], \tag{23}
\]

\[
\pi_2 (\Delta_T, \theta, r) = \left[ \frac{1}{\theta} - \frac{\Delta_T - r}{3} \right] \left[ \frac{1}{2} - \frac{(\Delta_T - r)\theta}{6} \right]. \tag{24}
\]

At date 2, as can readily be shown, in equilibrium Firm 1 licenses innovation \(\Delta_T\) from the innovator if and only if (iff) the payoff it can obtain if she buys the license is at least as large as its payoff if it does not buy the license: \(\pi_1 (\Delta_T, \theta, r) - z_T (\Delta_T, \theta, r) \geq \pi_1 (0, \theta, r)\).

At date 1, the foresighted innovator sets the highest license fee \(z_T\) that she can extract from Firm 1, subject to her buying the license, which is simply:

\[
z_T (\Delta_T, \theta, r) = \pi_1 (\Delta_T, \theta, r) - z_T (\Delta_T, \theta, r) = \left[ \frac{1}{\theta} + \frac{\Delta_T - r}{3} \right] \left[ \frac{1}{2} + \frac{(\Delta_T - r)\theta}{6} \right] - \frac{1}{2\theta}. \tag{25}
\]

The innovator chooses innovation \(\Delta_T^*\) to maximize the following payoff:

\[
Z_T = z_T (\Delta_T, \theta, r) + r \cdot d_1 (p_1, p_2, \theta) - K_T (\Delta_T), \tag{26}
\]

with the expected demand \(d_1 (p_1, p_2, \theta) = \frac{1}{2} + \frac{(\Delta_T - r)\theta}{6}\). Using expression (31), and taking the FOC with respect to \(\Delta_T\) and \(r\), yields the optimal innovation, royalty, and payoff for the innovator are:

\[
\Delta_T^* = \frac{3}{8 - \theta}, \tag{27}
\]

\[
r_T^* = \frac{6}{\theta(8 - \theta)}, \tag{28}
\]

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\[ Z_T^* = \frac{\theta + 1}{2\theta(8 - \theta)}. \]  

(29)

Under the targeted licensing with a fixed fee plus royalty contract, the licensee, Firm 1, will need to pay a per unit royalty in addition to a fixed fee. As in the main model, the optimal fixed fee is the difference between Firm 1’s access profits and no-access profits. The only difference here is that in the profit maximization for Firm 1, she has to pay a per unit royalty, \( r \). The equilibrium innovation level that the innovator chooses is \( \Delta_T^* = \frac{3}{8-\theta} \), which clearly suggests a similar relationship as in the main model - innovation \( \Delta_T^* \) is increasing in downstream competition, \( \theta \).

**Market-Wide Licensing.** Suppose now the innovator plans to license innovations to both downstream firms. In addition of charging a fixed licensing fee, the innovator imposes royalties in the licensing deal as well. We derive the equilibrium by backward induction.

*At date 3*, price competition takes place between firms 1 and 2. Specifically, Firm \( i \), \( i = 1, 2 \), chooses \( p_i \) to maximize its expected payoff, taking costs and innovations as given:

\[
\max_{p_i} \pi_i (\Delta_i, p_i, p_j, \theta, r) = \max_{p_i} (p_i - c + \Delta_M - r) d_i (p_i, p_j, \theta),
\]

with a similar deriving procedure as before, Firm \( i \)’s expected profits simplify to \( \pi_i (\Delta_{iM}, \Delta_{jM}, \theta) = 1/(2\theta) \).

*At date 2*, as can readily be shown, in equilibrium Firm \( i \) licenses innovation \( \Delta_M \) from the innovator if and only if (iff) the payoff it can obtain if she buys the license is at least as large as its payoff if it does not buy the license: \( \pi_i (\Delta_i, \Delta_j, \theta) - z_iM (\Delta_i, \Delta_j, \theta) \geq \pi_i (0, \Delta_j, \theta) \), with \( \Delta_i = \Delta_j = \Delta_M \).

*At date 1*, the foresighted innovator sets the highest license fee \( z_iM \) that she can extract from Firm \( i \), subject to both firms buying the license, which is simply:

\[
z_iM (\Delta_M, \theta) = \pi_i (\Delta_M, \Delta_M, \theta) - \pi_i (0, \Delta_M, \theta) = \frac{1}{2\theta} - \left[ \frac{1}{\theta} - \frac{\Delta_M - r}{3} \right] \left[ \frac{1}{2} - \frac{(\Delta_M - r)\theta}{6} \right].
\]

(31)

The innovator chooses innovation \( \Delta_M^* \) to maximize the following payoff:

\[
Z_M = r \cdot d_1 (p_1, p_2, \theta) + r \cdot d_2 (p_1, p_2, \theta) + z_{1M} (\Delta_M, \theta) + z_{2M} (\Delta_M, \theta) - K_M (\Delta_M).
\]

(32)

Using expression (31), and taking the FOC with respect to \( \Delta_M \) and \( r \) respectively, we obtain the following equilibrium results:
\[ \Delta^*_M = 1, \quad (33) \]

\[ r^*_T = 1 + \frac{3}{2\theta}, \quad (34) \]

\[ Z^*_M = \frac{1}{2} + \frac{1}{4\theta}. \quad (35) \]

Under market-wide licensing and a contract with a fixed fee plus royalty, a unique equilibrium exists, in which the innovator chooses innovation levels \( \Delta^*_M = 1 \), and the payoff to the innovator, simplifies to \( Z^*_M = \frac{1}{2} + \frac{1}{4\theta} \). The equilibrium innovation level is now constant, and the equilibrium licensing fee for the innovator is decreasing in downstream competition level, \( \theta \). One can see that while equilibrium innovation is now independent of competition under market-wide licensing, the key results are still similar to those of the main model.

**Targeted Licensing vs. Marketed-wide Licensing.** We proceed to compare the payoffs under targeted licensing and marketed-wide licensing as follows:

\[ \Delta Z = Z^*_T - Z^*_M = \frac{\theta + 1}{2\theta(8 - \theta)} - \left( \frac{1}{2} + \frac{1}{4\theta} \right). \quad (36) \]

Let \( \Delta Z = 0 \), clearly there is a threshold point of \( \theta \), \( \theta^* = 6.9 \), such that above this point, the targeted licensing dominates the market-wide licensing, i.e., \( \Delta Z \geq 0 \); while below this point, the market-wide licensing becomes optimal, i.e., \( \Delta Z > 0 \). Together with the above results under targeted and marketed-wide licensing, one can easily deduce that the equilibrium innovation has an U-shaped relationship with downstream competition. These key results under a fixed fee plus royal contract are equivalent to the results in our model where a fixed fee contract is applied. In particular, competition continues to increase the appeal of targeted licensing over market-wide licensing \((\partial (\Delta Z) / \partial \theta > 0)\). Overall, in the context of a fixed fee plus royalty contract, there exists a threshold level of competition \( \theta^* = 6.9 \), such that the innovator chooses market-wide licensing for all \( \theta \in (0, 6.9) \), and chooses targeted licensing for all \( \theta \in [6.9, 8) \). This further points to an U-shaped relationship between downstream competition and upstream innovation.

48
References


\[
Z_T^* - Z_M^*
\]

\[
h - \frac{1}{6}
\]

\[
\theta^*
\]

\[
\theta \in \left(0, \frac{1}{6}\right)
\]

\[
h \geq \frac{1}{6}
\]

**Figure 1:** Product Market Competition and Licensing Strategy
Figure 2: Product Market Competition and Innovation

a1) $h \in (0, \frac{1}{6}), \theta^* (h) \geq \frac{9}{4}$

a2) $h \in (0, \frac{1}{6}), \theta^* (h) < \frac{9}{4}$

b) $h \geq \frac{1}{6}$
# Appendix

## Table 1 Sample Distribution and Number of Downstream Industries

<table>
<thead>
<tr>
<th>Two-digit NAICS code</th>
<th>Industry group name</th>
<th>No. of firm-years</th>
<th>% of Sample</th>
<th>No. of downstream industries</th>
</tr>
</thead>
<tbody>
<tr>
<td>11</td>
<td>Agriculture, Forestry, Fishing and Hunting</td>
<td>57</td>
<td>0.23</td>
<td>80</td>
</tr>
<tr>
<td>21</td>
<td>Mining</td>
<td>577</td>
<td>2.31</td>
<td>42</td>
</tr>
<tr>
<td>22</td>
<td>Utilities</td>
<td>189</td>
<td>0.76</td>
<td>16</td>
</tr>
<tr>
<td>23</td>
<td>Construction</td>
<td>66</td>
<td>0.26</td>
<td>63</td>
</tr>
<tr>
<td>31</td>
<td>Manufacturing I</td>
<td>777</td>
<td>3.11</td>
<td>78</td>
</tr>
<tr>
<td>32</td>
<td>Manufacturing II</td>
<td>5925</td>
<td>23.71</td>
<td>191</td>
</tr>
<tr>
<td>33</td>
<td>Manufacturing</td>
<td>13677</td>
<td>54.74</td>
<td>226</td>
</tr>
<tr>
<td>42</td>
<td>Wholesale Trade</td>
<td>203</td>
<td>0.81</td>
<td>231</td>
</tr>
<tr>
<td>44</td>
<td>Retail Trade I</td>
<td>37</td>
<td>0.15</td>
<td>41</td>
</tr>
<tr>
<td>45</td>
<td>Retail Trade II</td>
<td>15</td>
<td>0.06</td>
<td>47</td>
</tr>
<tr>
<td>48</td>
<td>Transportation and Warehousing</td>
<td>150</td>
<td>0.60</td>
<td>68</td>
</tr>
<tr>
<td>49</td>
<td>Transportation and Warehousing</td>
<td>5</td>
<td>0.02</td>
<td>25</td>
</tr>
<tr>
<td>51</td>
<td>Information</td>
<td>1357</td>
<td>5.43</td>
<td>54</td>
</tr>
<tr>
<td>52</td>
<td>Finance and Insurance</td>
<td>488</td>
<td>1.95</td>
<td>45</td>
</tr>
<tr>
<td>53</td>
<td>Real Estate and Rental and Leasing</td>
<td>258</td>
<td>1.03</td>
<td>48</td>
</tr>
<tr>
<td>54</td>
<td>Professional, Scientific and Technical Services</td>
<td>819</td>
<td>3.28</td>
<td>92</td>
</tr>
<tr>
<td>56</td>
<td>Administration, Business Support &amp; Waste Management Services</td>
<td>162</td>
<td>0.65</td>
<td>69</td>
</tr>
<tr>
<td>61</td>
<td>Educational Services</td>
<td>22</td>
<td>0.09</td>
<td>21</td>
</tr>
<tr>
<td>62</td>
<td>Healthcare and Social Assistance</td>
<td>143</td>
<td>0.57</td>
<td>37</td>
</tr>
<tr>
<td>71</td>
<td>Arts, Entertainment and Recreation</td>
<td>4</td>
<td>0.02</td>
<td>22</td>
</tr>
<tr>
<td>72</td>
<td>Accommodation and Food Services</td>
<td>56</td>
<td>0.22</td>
<td>8</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td></td>
<td><strong>24,987</strong></td>
<td><strong>100.00</strong></td>
<td></td>
</tr>
</tbody>
</table>

This table reports the number of firm-year observations within each two-digit NAICS industry group in our final sample. This table also reports for each two-digit NAICS industry group the mean values of the number of downstream industries (defined at the five-digit NAICS level).
Table 2 Variable Definitions and Summary Statistics

Panel A provides definitions of the main variables. Panel B reports summary statistics for variables constructed using a sample of U.S. public firms. Upstream firm innovation and control variables are measured from 1976-2006. Downstream industry competition is measured based on the whole sample from Compustat from 1976-2006.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Measures of Innovation</strong></td>
<td></td>
</tr>
<tr>
<td>CITE_WEIGHT_PAT</td>
<td>The patent number of a firm within a year weighted by the citations of these patents</td>
</tr>
<tr>
<td>CITE_PER_PAT</td>
<td>The total citations of a firm within a year divided by the total patent number of the firm</td>
</tr>
<tr>
<td>CITE_TOTAL</td>
<td>The total citations of a firm within a year</td>
</tr>
<tr>
<td><strong>Measures of Downstream Competition</strong></td>
<td></td>
</tr>
<tr>
<td>DOWN_COMP</td>
<td>One minus the Lerner index for a downstream industry within a year</td>
</tr>
<tr>
<td><strong>Measures of Control Variables</strong></td>
<td></td>
</tr>
<tr>
<td>RDTA</td>
<td>R&amp;D intensity is defined as research and development expenditures divided by book value of total assets measured at the end of fiscal year</td>
</tr>
<tr>
<td>LEV</td>
<td>Leverage ratio is defined as book value of debt divided by book value of total assets measured at the end of fiscal year</td>
</tr>
<tr>
<td>ROA</td>
<td>Return on assets is defined as operating income before depreciation divided by book value of total assets, measured at the end of fiscal year</td>
</tr>
<tr>
<td>CAPXTA</td>
<td>Capital expenditures scaled by book value of total assets measured at the end of fiscal year</td>
</tr>
<tr>
<td>UP_COMP</td>
<td>One minus the Herfindahl index of four-digit SIC industry j to which firm I belongs, measured at the end of fiscal year t.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variable</th>
<th>10%</th>
<th>Mean</th>
<th>Median</th>
<th>90%</th>
<th>SD</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>CITE_WEIGHT_PAT</td>
<td>0</td>
<td>0.1362</td>
<td>0.00239</td>
<td>0.0589</td>
<td>0.777</td>
<td>24,845</td>
</tr>
<tr>
<td>CITE_PER_PAT</td>
<td>0.62</td>
<td>15.548</td>
<td>10.485</td>
<td>33.178</td>
<td>20.456</td>
<td>24,845</td>
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<tr>
<td>CITE_TOTAL</td>
<td>1.0463</td>
<td>423.6158</td>
<td>37.99</td>
<td>629.598</td>
<td>2335.598</td>
<td>24,845</td>
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<tr>
<td>DOWN_COMP</td>
<td>0.682</td>
<td>0.7687</td>
<td>0.779</td>
<td>0.844</td>
<td>0.071</td>
<td>24,845</td>
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<td>RDTA</td>
<td>0.00934</td>
<td>0.1081</td>
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<td>20,780</td>
</tr>
<tr>
<td>LEV</td>
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<td>0.1862</td>
<td>0.45</td>
<td>0.2015</td>
<td>24,785</td>
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<tr>
<td>MB</td>
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<td>2.257</td>
<td>1.458</td>
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<td>2.372</td>
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<td>ROA</td>
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<td>0.0442</td>
<td>0.121</td>
<td>0.24</td>
<td>0.292</td>
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<td>CAPXTA</td>
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<td>0.0503</td>
<td>0.124</td>
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<td>UP_COMP</td>
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<td>0.848</td>
<td>0.9258</td>
<td>0.987</td>
<td>0.19</td>
<td>24,914</td>
</tr>
</tbody>
</table>
Table 3 Downstream Industry Competition and Upstream Firm Innovation
Panel A presents coefficients estimates of regressions which examine the effect of downstream industry competition on upstream firm innovation (model (14)). The dependent variable is the citation-weighted patents for firm $i$ in year $t$. In Panel A, column (1) presents the results with year and industry fixed effects by using negative binomial method, and column 2 further includes firm level controls. Column (3) presents the results by using OLS, and columns (4) and (5) include year and industry fixed effects, and control for firm characteristics respectively. Finally, columns (6) and (7) show the results by using Poisson model and control for year and industry fixed effects, and firm characteristics respectively. The sample period is from 1976-2006. Panel B reports the results of the differences in the impact of competition on innovation. Columns (1) – (3) show the moderating role of firm size. And columns (4) – (6) present the results of the impact of upstream industry innovation intensity. All variables are defined in Table 1. We report t-statistics using standard errors adjusted for within-firm clustering in parentheses below the coefficients estimates. Significance at the 10%, 5%, and 1% level is indicated by *, **, ***, respectively.

Panel A: The impact of downstream competition on upstream innovation

<table>
<thead>
<tr>
<th>Method</th>
<th>Negative Binomial</th>
<th>Negative Binomial</th>
<th>Poisson</th>
<th>Poisson</th>
<th>OLS</th>
<th>OLS</th>
<th>OLS</th>
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</thead>
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<tr>
<td>Dependent variable</td>
<td>CITE_WEIGHT_PAT (1)</td>
<td>CITE_WEIGHT_PAT (2)</td>
<td>CITE_WEIGHT_PAT (3)</td>
<td>CITE_WEIGHT_PAT (4)</td>
<td>ln(CITE_WEIGHT_PAT) (5)</td>
<td>ln(CITE_WEIGHT_PAT) (6)</td>
<td>ln(CITE_WEIGHT_PAT) (7)</td>
</tr>
<tr>
<td></td>
<td>(3.674)</td>
<td>(3.953)</td>
<td>(1.806)</td>
<td>(2.861)</td>
<td>(1.326)</td>
<td>(1.510)</td>
<td>(0.908)</td>
</tr>
<tr>
<td>$DOWN_COMP^2$</td>
<td>6.659***</td>
<td>5.677**</td>
<td>2.680**</td>
<td>4.22**</td>
<td>1.983**</td>
<td>2.237**</td>
<td>1.004*</td>
</tr>
<tr>
<td></td>
<td>(2.532)</td>
<td>(2.760)</td>
<td>(1.390)</td>
<td>(2.160)</td>
<td>(0.830)</td>
<td>(0.930)</td>
<td>(0.556)</td>
</tr>
<tr>
<td>$RDTX$</td>
<td>-11.137***</td>
<td>-10.445***</td>
<td>-0.068*</td>
<td>-0.139*</td>
<td>(2.746)</td>
<td>(3.513)</td>
<td>(0.050)</td>
</tr>
<tr>
<td></td>
<td>(2.746)</td>
<td>(3.513)</td>
<td>(0.050)</td>
<td>(0.070)</td>
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<td></td>
</tr>
<tr>
<td>$LEV$</td>
<td>0.203</td>
<td>0.257</td>
<td>0.010</td>
<td>0.063*</td>
<td>(0.538)</td>
<td>(0.481)</td>
<td>(0.026)</td>
</tr>
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<td>(0.538)</td>
<td>(0.481)</td>
<td>(0.026)</td>
<td>(0.032)</td>
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<td>$MB$</td>
<td>-0.240***</td>
<td>-0.207***</td>
<td>-0.004***</td>
<td>-0.004***</td>
<td>(0.077)</td>
<td>(0.065)</td>
<td>(0.001)</td>
</tr>
<tr>
<td></td>
<td>(0.077)</td>
<td>(0.065)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$ROA$</td>
<td>3.404***</td>
<td>2.073***</td>
<td>0.024</td>
<td>0.030</td>
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<td>(0.753)</td>
<td>(0.025)</td>
</tr>
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<td></td>
<td>(0.613)</td>
<td>(0.753)</td>
<td>(0.025)</td>
<td>(0.025)</td>
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<tr>
<td>$CAPXTA$</td>
<td>3.995**</td>
<td>1.785</td>
<td>0.155</td>
<td>0.096</td>
<td>(1.982)</td>
<td>(1.800)</td>
<td>(0.147)</td>
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<td>(1.982)</td>
<td>(1.800)</td>
<td>(0.147)</td>
<td>(0.155)</td>
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<tr>
<td>$UP_COMP$</td>
<td>-3.358*</td>
<td>-2.565</td>
<td>0.326*</td>
<td>-0.134</td>
<td>(1.972)</td>
<td>(2.202)</td>
<td>(0.188)</td>
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<tr>
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<td>(1.972)</td>
<td>(2.202)</td>
<td>(0.188)</td>
<td>(0.100)</td>
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<td></td>
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</tr>
<tr>
<td>$UP_COMP^2$</td>
<td>2.316</td>
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<td>-0.247</td>
<td>(0.69)</td>
<td>(1.578)</td>
<td>(1.815)</td>
<td>(0.165)</td>
</tr>
<tr>
<td></td>
<td>(1.578)</td>
<td>(1.815)</td>
<td>(0.165)</td>
<td>(0.103)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Year fixed effects | Yes | Yes | Yes | Yes | No | No | Yes |
Industry fixed effects | Yes | Yes | Yes | Yes | No | No | Yes |
Number of clusters | 3,718 | 2,716 | 3,718 | 2,716 | 3,718 | 2,716 | 2,716 |
Observations | 24,845 | 17,743 | 24,845 | 17,743 | 24,845 | 17,743 | 17,743 |
Panel B: The differences in the impact of downstream competition on upstream innovation

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>ln(CITE_WEIGHT_PAT) (1)</th>
<th>ln(CITE_WEIGHT_PAT) (2)</th>
<th>ln(CITE_WEIGHT_PAT) (3)</th>
<th>ln(CITE_WEIGHT_PAT) (4)</th>
<th>ln(CITE_WEIGHT_PAT) (5)</th>
<th>ln(CITE_WEIGHT_PAT) (6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>DOWN_COMP</td>
<td>0.011</td>
<td>2.440*</td>
<td>3.534</td>
<td>-3.656**</td>
<td>-1.161</td>
<td>-1.727*</td>
</tr>
<tr>
<td></td>
<td>(0.021)</td>
<td>(1.516)</td>
<td>(2.188)</td>
<td>(1.609)</td>
<td>(0.757)</td>
<td>(0.949)</td>
</tr>
<tr>
<td>DOWN_COMP_SQ</td>
<td>-0.003</td>
<td>-1.388</td>
<td>-2.011</td>
<td>2.118**</td>
<td>0.700</td>
<td>1.069*</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.871)</td>
<td>(1.287)</td>
<td>(1.019)</td>
<td>(0.474)</td>
<td>(0.589)</td>
</tr>
<tr>
<td>SIZE</td>
<td>1.682**</td>
<td>1.739**</td>
<td>2.709**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.674)</td>
<td>(0.793)</td>
<td>(1.158)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SIZE*DOWN_COMP_P</td>
<td>-3.616**</td>
<td>-3.700**</td>
<td>-5.894**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.681)</td>
<td>(1.831)</td>
<td>(2.662)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SIZE*DOWN_COMP_P_SQUARE</td>
<td>2.069*</td>
<td>2.115**</td>
<td>3.369**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.068)</td>
<td>(1.060)</td>
<td>(1.532)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>INNO</td>
<td></td>
<td></td>
<td></td>
<td>-1.467**</td>
<td>-1.724**</td>
<td>-4.093*</td>
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## Table 4 Robustness Analysis

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- Year fixed effects: Yes
- Industry fixed effects: Yes
- Estimation method: OLS
- Number of clusters: 3,718
- Observations: 24,914

### Panel B: Regression using sample period 1976-2001

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- Year fixed effects: Yes
- Industry fixed effects: Yes
- Estimation method: OLS
- Number of clusters: 3,718
- Observations: 24,914

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Panel C: Regression using sample of four-digit SIC 2000 – 3999 (Aghion et al. (2005))

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Panel D: Regression using TNIC-based competition

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Table 5: Reductions of Import Tariff Rates and Upstream Firm Innovation

This table presents coefficients estimates of tariff rate reductions on upstream firm innovation. The dependent variable is upstream firm innovation. In columns 1 and 2, SHOCK is the average of competitive shocks from downstream industries \( k \) related to an upstream industry \( j \) by year \( t \). And a competitive shock in a downstream industry is defined if a tariff rate reduction in the downstream industry \( k \) by time \( t \) that is larger than three times the median tariff rate reduction in that industry. In columns 3 (and 4), a competitive shock in a downstream industry is defined if a tariff rate reduction in the downstream industry \( k \) by time \( t \) that is larger than two (one and a half) times the median tariff rate reduction in that industry. We report t-statistics using standard errors adjusted for within-firm clustering in parentheses below the coefficient estimates. Significance at the 10%, 5%, and 1% is indicated by *, **, and *** respectively.

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### Table 6 Licensing Strategy and Downstream Competition

#### Panel A: Downstream competition, licensing strategy, and upstream innovation

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#### Panel B: Downstream competition and licensing strategy

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