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ABSTRACT

We study how competition between two downstream firms affects an upstream innovator's innovation strategy, which includes selecting how much innovation to produce and whether to license this innovation to one (targeted licensing) or both (market-wide licensing) downstream competitors. Our model points to a U-shaped relationship between downstream competition and upstream innovation: at low levels of competition, market-wide licensing is optimal and competition reduces innovation, while at high levels of competition targeted licensing is optimal and competition increases innovation. Empirical analysis using a large panel of US data provides clear support for these predictions linking competition, innovation and licensing.

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1 Introduction

Understanding how competition affects innovation is one of the oldest and most elusive theoretical and empirical challenges in industrial organization and innovation economics. Schumpeter (1934, 1942) famously argued that competition weakens incentives to innovate by lowering monopoly rents. In contrast, Stigler's (1958) survivor principle argued that competition promotes innovation by weeding out less innovative, and hence less efficient, firms, and Arrow (1962) suggested that incumbent monopolists may have weaker innovation incentives because they internalize the cannibalization of their own existing products.[1] Empirical evidence is equally ambiguous: empirical studies find positive, negative, or non-monotonic relations between innovation and competition depending on the empirical context.[2]

This paper offers a new perspective on this question. Our analysis is motivated by the fact that innovations often take place in markets upstream from those in which the relevant product market competition occurs. In these settings, intellectual property rights allow for the innovations to be licensed to downstream firms in technology markets. In the chemical industry, for example, 79% of technology used is obtained through licensing (Arora and Fosfuri, 2000). We develop and test a model based on these insights that links competition, technology markets, and innovation.

In particular, we study how downstream competition between two product market rivals impacts an upstream innovator's optimal licensing and innovation strategies. The model delivers a non-monotonic, U-shaped relation between downstream competition and upstream innovation. Our empirical analysis confirms these predictions. Taken together, the results highlight the subtle connection between competition and innovation across markets that helps to explain the tenuous relationship emerging from the empirical literature.

We consider a market for technology in which an upstream innovator serves two downstream firms exogenously located at either end of a Hotelling (1929) line. The innovator makes an investment in a cost-reducing innovation which, once generated, can be licensed in the downstream market by one of two means: either the innovation is licensed to a single competitor through "targeted" licensing, or it is licensed to both competitors at the same time, which we call "market-wide" licensing. The upstream innovator chooses a licensing strategy and innovation policy to maximize her profits, which in turn

[1] More recent work 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; Hermalin, 1992; Schmidt, 1997; Raith, 2003; Baggs and Bettignies, 2007; Bettignies and Ross, 2014).

[2] Competition has a positive impact on innovation in Geroski (1990), Bertschek (1995) and Blundell *et al.* (1999); a negative effect in Hashmi (2013), and an inverted-U effect in Aghion *et al.* (2005). We discuss our relation to Aghion *et al.* (2005) in more detail below.

are a function of the degree of competition in the downstream market. The strategic implications of the licensing choice are critical: targeted licensing allows a single downstream firm to *gain* a cost *advantage* over its rival, which allows it to steal market share. In contrast, market-wide licensing allows each downstream firm to *avoid* facing both cost and demand *disadvantages* relative to its rival. In a sense, targeted licensing confers an offensive advantage while market-wide licensing confers a defensive advantage. We exploit this difference between licensing strategies to derive and explain two key insights linking competition and innovation.

The first insight links downstream competition to optimal licensing arrangements. 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. This occurs because competition has two offsetting effects on licensing revenue. On the one hand, it leads downstream firms to lower their prices and hence their 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 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 a sole licensee's payoff, which increases that firm's willingness to pay for the license and hence the innovator's licensing revenue. Under market-wide licensing, business stealing increases both firms' willingness to pay by decreasing the payoff 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 come 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 licensing, 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 smaller 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 differs across licensing strategies. Competition affects the innovator's marginal benefit from innovation through business stealing and rent reduction effects in a similar manner to that 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 show that the relationship between downstream 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. In sum, the model predicts a non-monotonic, U-shaped relation between downstream competition and upstream innovation, with a switch-point driven by licensing considerations.

The second part of our analysis tests two key predictions from our model using a large panel of publicly traded U.S. firms over the period $1976 - 2006$. The first prediction regards the U-shaped relation between downstream competition and upstream innovation. Simple descriptive tests linking patenting activity to a downstream industry's Lerner index clearly reveal a U-shaped relationship between downstream competition and upstream innovation. But tests of this nature are fraught with endogeneity concerns, because future profitability in an industry affects both the incentive to innovate as well as the incentives for challengers to enter the market. To address these, we use the reductions in import tariff rates as an exogenous shock to the competitive structure of an industry. The key to our identification strategy rests in the fact that firms in industries with large reductions in import tariff rates face higher competition, but the reduction of import tariffs has no direct impact on the optimal choice of licensing strategies except through the change in downstream demand conditions.

Overall our identification strategy supports the idea that downstream competition has a non-linear causal impact on upstream innovation. Regardless of whether we model the threshold analytically or simply split the data at the median level of competitiveness, we find that innovation decreases with competition below the threshold and increases with competition above it.

The second piece of our empirical analysis implicates licensing choices as a key channel behind the U-shaped relation. Consistent with the theoretical model, data on strategic alliance and licensing deals illustrates 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.

Perhaps closest to our paper is Aghion *et al.*'s (2005) work, which identifies an inverted-U relationship between competition and innovation. In a way, the U-shaped relationship between downstream competition and upstream innovation predicted by our model is the opposite of the relationship derived in Aghion *et al.* (2005). Although both analyses model innovation as a cost-reducing process, the critical difference lies in the fact that Aghion *et al.* (2005) study the connection between product market competition and innovation within a given industry, whereas in our analysis, competitors in a downstream market are effectively renting the right to use an external innovation on terms that are dictated by the upstream innovator. Our rent-reduction and business stealing effects of competition are similar to their Schumpeterian and escape-competition effects in their model, although they emerge explicitly from the strategic interactions between downstream competitors in our framework.

Our work is also related to the literature on "outsider patentee" licensing, which considers an innovation undertaken by an upstream innovator who then licenses the innovation to firms competing in the downstream product market,[3] and to the "insider patentee" licensing literature which examines the voluntary transfer of technology/innovation from one downstream competitor to another.[4] In particular, Fauli-Oller *et al.* (2011) suggests that mergers in the downstream market (and the concomitant reduction in competition) should be associated with increased R&D investments by the upstream innovator supplying *all* of the downstream competitors.[5] We depart from these lines of work by endogenizing *both* innovation decisions *and* licensing decisions. This allows us to unpack the specific, simultaneous and related effects of competition on licensing and innovation strategies.

The balance of the paper proceeds as follows. In Section 2, we set up the basic model and derive

[3]See Kamien and Tauman (1984, 1986) Katz and Shapiro (1986), Muto (1993), Schmitz (2002), Poddar and Sinha (2004), Bagchi (2008), Farrell and Shapiro (2008), Allain *et al.* (2011), Fauli-Oller *et al.* (2011), Fauli-Oller and Sandonis (2012), and Chatain (2014).

[4]See Gallini (1984), Gallini and Winter (1985), Katz and Shapiro (1987), Fauli-Oller and Sandonis (2002), Arora and Fosfuri (2003), and Erkal (2005).

[5]See also the recent work of Chatain (2014), which 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 our use of 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; and in our endogenizing of both innovation and licensing decisions.

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 the data required to test the model, while in Section 5, we present the main empirical findings. Finally, Section 6 concludes. 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. 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 $\theta = 1/t$ which captures the degree of homogeneity between products, 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 work 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, θ, as our measure of competition. We restrict our attention to value of $\theta \in \Theta$ with $\Theta \equiv (0, 9/2)$, which ensures strict concavity of all maximization programs as well as positive equilibrium prices, demands and profits (see proofs of Lemmas 1 and 2).[6]

Innovation. Upstream from the two product market competitors, an innovator is working on an innovation that can be licensed to the downstream firms. For simplicity and concreteness, we refer to this as a cost-reducing innovation, but a value-enhancing innovation works same here as it also leads to quality improvement of downstream firms' products. The innovator has two alternatives. Under *targeted licensing*, she chooses innovation level Δ_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.[7] Under *market-wide licensing*, she chooses innovation level Δ_M and licenses it to both firms 1 and 2. An innovation Δ benefits the licensees by reducing their marginal cost of production by Δ; 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 C we also consider

[6] In setting this type of simplifying parametric restriction we follow Raith (2003) and others.

[7] 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) review of the foreclosure literature.

licensing contracts based on auctions, and on two-part tariffs; and show that qualitatively similar results continue to hold.

Thus, we assume that under market-wide licensing innovation Δ_M is licensed to firms 1 and 2, respectively, for license fees z_{1M} and z_{2M}; and that under targeted licensing, innovation Δ_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:

$$\max_{p_i} \pi_i \left(\Delta_i, p_i, p_j, \theta\right) = \max_{p_i} \left(p_i - c + \Delta_M\right) d_i \left(p_i, p_j, \theta\right), \tag{2}$$

with expected demand $d_i \left(p_i, p_j, \theta\right)$ 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:

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

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

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

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 Δ_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:

$$z_{iM} (\Delta_M, \theta) = \pi_i (\Delta_M, \Delta_M, \theta) - \pi_i (0, \Delta_M, \theta) = \frac{1}{2\theta} - \left[\frac{1}{\theta} - \frac{\Delta_M}{3}\right]\left[\frac{1}{2} - \frac{\Delta_M \theta}{6}\right]. \tag{5}$$

Under market-wide licensing, Firm i takes as given that Firm j has access to innovation Δ_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 Δ_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.[8] The innovator chooses innovation Δ_M^* to maximize the following payoff:

$$Z_M = z_{1M} (\Delta_M, \theta) + z_{2M} (\Delta_M, \theta) - K_M (\Delta_M). \tag{6}$$

Using expression (6), and taking the FOC with respect to Δ_M, yields Δ_M^* such that:

$$-\frac{\partial \pi_1}{\partial \Delta_2} (0, \Delta_M^*, \theta) - \frac{\partial \pi_2}{\partial \Delta_1} (0, \Delta_M^*, \theta) = \frac{\partial K}{\partial \Delta_M} (\Delta_M^*). \tag{7}$$

Clearly, a marginal increase in innovation Δ_M has no impact on symmetric profits: $\frac{\partial \pi_i}{\partial \Delta_M} (\Delta_M, \Delta_M, \theta) = \frac{\partial (1/2\theta)}{\partial \Delta_M} = 0$. This is because an increase in Δ_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 Δ_M does reduce laggard profits for firms 1 and 2. An increase in Δ_M reduces the profits that Firm 1 (resp. 2) makes if it does not license the innovation,

[8] 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 (C.3) 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 (C.3) 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 verifiy that - in our Hotelling framework, at the equilibrium innovation level $\Delta_M^* = \frac{6}{9+2\theta}$ - 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.

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 Δ_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 the left-hand side of (7). The right-hand side represents the innovator's marginal cost of innovating. As shown in Appendix B, solving the FOC for Δ_M^* yields a unique equilibrium:

Lemma 1 *Under market-wide licensing, a unique equilibrium exists, in which the innovator chooses innovation levels* $\Delta_M^* = \frac{6}{9+2\theta}$. *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* $z_{1M} = z_{2M} = \frac{2(9+\theta)}{(9+2\theta)^2}$, *and* $Z_M^* = \frac{2}{(9+2\theta)} - h$, *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 Δ_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 (4) as $\pi_1(\Delta_T, 0, \theta)$ and $\pi_2(0, \Delta_T, \theta)$, respectively.

At date 2, in equilibrium Firm 1 licenses innovation Δ_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: $\pi_1(\Delta_T, 0, \theta) - \overline{z}_{12}(\Delta_T, 0, \theta) \geq \pi_1(0, 0, \theta)$.

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

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

Under targeted licensing, Firm 1 takes as given that Firm 2 does not have access to innovation Δ_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 Δ_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.[9]

[9] 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 C, where similar results are shown to arise.

The innovator chooses innovation Δ_T^* to maximize the following payoff:

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

Using expression (9), and taking the FOC with respect to Δ_T, yields Δ_T^* such that:[10]

$$\frac{\partial \pi_1}{\partial \Delta_1}(\Delta_T^*, 0, \theta) = \frac{\partial K_T}{\partial \Delta_T}(\Delta_T^*). \tag{10}$$

Under targeted licensing, the innovator's marginal benefit from innovation Δ_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 B, solving the FOCs for Δ_T^*, one obtains a unique equilibrium:

Lemma 2 *Under targeted licensing, a unique equilibrium exists, in which the innovator chooses innovation level* $\Delta_T^* = \frac{3}{9-\theta}$. *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.

[10] Note that Δ_T has no impact on firm 1's no-access profits: $\partial \pi_1(0, 0, \theta)/\partial \Delta_T = 0$.

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:[11][12]

$$\begin{aligned}
\frac{\partial Z_M^*}{\partial \theta} &= \sum_{i=1}^{2} \frac{\partial z_{iM}(\Delta_M, \theta)}{\partial \theta} = \sum_{i=1}^{2} \frac{\partial \left[\pi_i(\Delta_M, \Delta_M, \theta) - \pi_i(0, \Delta_M, \theta)\right]}{\partial \theta} \qquad (11) \\
&= \sum_{i=1}^{2} \left[\frac{\partial P_i(\Delta_M, \Delta_M, \theta)}{\partial \theta} d_i(\Delta_M, \Delta_M, \theta) - \frac{\partial P_i(0, \Delta_M, \theta)}{\partial \theta} d_i(0, \Delta_M, \theta)\right] \\
&\quad + \sum_{i=1}^{2} \left[-\frac{\partial d_i(0, \Delta_M, \theta)}{\partial \theta} P_i(0, \Delta_M, \theta)\right]
\end{aligned}$$

and:

$$\begin{aligned}
\frac{\partial Z_T^*}{\partial \theta} &= \frac{\partial z_T^*(\Delta_T, \theta)}{\partial \theta} = \frac{\partial \left[\pi_1(\Delta_T, 0, \theta) - \pi_1(0, 0, \theta)\right]}{\partial \theta} \\
&= \left[\frac{\partial P_1(\Delta_T, 0, \theta)}{\partial \theta} d_1(\Delta_T, 0, \theta) - \frac{\partial P_1(0, 0, \theta)}{\partial \theta} d_1(0, 0, \theta)\right] \qquad (12) \\
&\quad + \left[\frac{\partial d_1(\Delta_T, 0, \theta)}{\partial \theta} P_1(\Delta_T, 0, \theta)\right].
\end{aligned}$$

Competition affects the innovator's licensing payoffs in two primary ways. First, it induces firms to lower their prices: using expression (4), one can see that regardless of the values of Δ_i and Δ_j, $\partial P_i(\Delta_i, \Delta_j, \theta)/\partial\theta = -1/\theta^2 < 0$. 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

[11] 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: $\partial d_i(\Delta, \Delta, \theta)/\partial\theta = 0$.

[12] 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 $-\Delta_T/(6\theta)$.[13]

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): $\frac{\partial d_i}{\partial\theta} = \frac{(\Delta_i - \Delta_j)}{6} \gtrless 0$ iff $\Delta_i \gtrless \Delta_j$, and $\frac{\partial d_i}{\partial\theta} = 0$ 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 $-\frac{\partial d_i(0,\Delta_M,\theta)}{\partial\theta} P_i(0, \Delta_M, \theta) = \Delta^*_M/(6\theta) - (\Delta^*_M)^2/18 > 0$. 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 $\frac{\partial d_1(\Delta_T,0,\theta)}{\partial\theta} P_1(\Delta_T, 0, \theta) = \Delta_T/(6\theta) + (\Delta_T)^2/18 > 0$.

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

[13] 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 $Z_T^* = \frac{1}{18-2\theta}$ 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:[14]

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 $\partial\theta^*(h)/\partial h < 0$, 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 Sections 4 and 5.

[14] Some further thoughts on this licensing tradeoff, and how it is affected by downstream competition, are presented in Appendix C.

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 of licenses is consistent with Bagchi (2008), which illustrates 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:[15]

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, $\Delta_T^* = \frac{3}{9-\theta}$, 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 (5) and (7), 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:

$$\begin{aligned}\sum_{i=1}^{2} \frac{\partial z_{iM}(\Delta_M, \theta)}{\partial \Delta_M} &= \sum_{i=1}^{2} \left[-\frac{\partial \pi_i}{\partial \Delta_j}(0, \Delta_M, \theta)\right] \\ &= \sum_{i=1}^{2} \left[-\frac{\partial d_i}{\partial \Delta_j}(\theta) P_i(0, \Delta_M, \theta) - \frac{\partial P_i}{\partial \Delta_j} d_i(0, \Delta_M, \theta)\right] \\ &= \sum_{i=1}^{2} \left[\frac{\theta}{6} P_i(0, \Delta_M, \theta) + \frac{1}{3} d_i(0, \Delta_M, \theta)\right],\end{aligned} \tag{13}$$

[15]The threshold value $\theta^{**} = 9/4$ is obtained simply by solving $\Delta_M^* = \frac{6}{9+2\theta} = \frac{3}{9-\theta} = \Delta_T^*$ for θ.

and:

$$\begin{aligned}\frac{\partial z_{1T}(\Delta_T,\theta)}{\partial \Delta_T} &= \frac{\partial \pi_1}{\partial \Delta_1}(\Delta_T,0,\theta) \\ &= \frac{\partial d_1}{\partial \Delta_1}(\theta) P_1(\Delta_T,0,\theta) + \frac{\partial P_1}{\partial \Delta_1} d_1(\Delta_T,0,\theta) \\ &= \frac{\theta}{6} P_1(\Delta_T,0,\theta) + \frac{1}{3} d_1(\Delta_T,0,\theta).\end{aligned} \tag{14}$$

Consider the innovator's market-wide licensing revenue from Firm i. Increasing innovation Δ_M increases Firm i's willingness to pay for the innovation by increasing the cost advantage that its rival Firm j will have if Firm i *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: $\frac{\partial P_j}{\partial \Delta_j} = \frac{1}{3} > 0$ and $\frac{\partial P_i}{\partial \Delta_j} = -\frac{1}{3} < 0$; 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 Δ_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 $\frac{\partial d_1}{\partial \Delta_1}(\theta) P_1(\Delta_T,0,\theta) > 0$. 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 θ, 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:

$$\sum_{i=1}^{2} \partial\left[-\frac{\partial \pi_i(0,\Delta_M,\theta)}{\partial \Delta_j}\right] / \partial\theta = \sum_{i=1}^{2}\left[\begin{array}{c} \frac{\partial d_i(0,\Delta_M,\theta)}{\partial\theta}\left[-\frac{\partial P_i}{\partial \Delta_j}\right] + \frac{\partial P_i(0,\Delta_M,\theta)}{\partial\theta}\left[-\frac{\partial d_i}{\partial \Delta_j}\right] \\ +\left[-\frac{\partial^2 d_i}{\partial \Delta_j \partial\theta}\right] P_i(0,\Delta_M,\theta) \end{array}\right], \tag{15}$$

and:

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

The degree of competition θ - 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.[16] As shall now become clear, 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 Δ_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.[17] 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 Δ_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 Δ_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 Δ_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.[18] Under market-wide licensing, this effect exacerbates the decrease

[16] Note from above that $\frac{\partial P_i}{\partial\Delta_i}=\frac{1}{3}$ and $\frac{\partial P_i}{\partial\Delta_j}=-\frac{1}{3}$ are independent of competition θ, and hence $\frac{\partial^2 P_i}{\partial\Delta_j\partial\theta}=\frac{\partial^2 P_i}{\partial\Delta_i\partial\theta}=0$.

[17] This effect is related to what Gosh *et al.* (2015) call "share-reduction effect" in the context of continuous improvement versus discrete innovation.

[18] 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 Δ_M. Under targeted licensing, this effect amplifies the increase in Firm 1's leader demand associated with an increase in Δ_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 (4) 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 $\left[-\frac{\partial^2 d_i}{\partial \Delta_j \partial \theta}\right] P_i\left(0, \Delta_M, \theta\right) = 1/\left(6\theta\right) - \Delta_M/18 > 0$. This effect is relatively weak, in the sense that it fails to outweigh the negative impact of rent reduction, which simplifies to $\frac{\partial P_i(0,\Delta_M,\theta)}{\partial \theta}\left[-\frac{\partial d_i}{\partial \Delta_j}\right] = -1/\left(6\theta\right) < 0$. Together these two effects imply a *negative* impact of competition on the marginal benefit from innovation; and the business stealing effect, which simplifies to $\frac{\partial d_i(0,\Delta_M,\theta)}{\partial \theta}\left[-\frac{\partial P_i}{\partial \Delta_j}\right] = -\Delta_M/18 < 0$, exacerbates this negative impact. Thus, under market-wide competition decreases the innovator's marginal benefit from innovating, thereby reducing equilibrium innovation Δ_M^*.

In contrast, under targeted licensing, the impact of increased business stealing can be shown to simplify to $\frac{\partial^2 d_1}{\partial \Delta_1 \partial \theta} P_1\left(\Delta_T, 0, \theta\right) = 1/\left(6\theta\right) + \Delta_T/18 > 0$. It is relatively strong in that is does outweigh the negative impact of rent reduction (which itself is the same under both licensing strategies), $\frac{\partial P_1(\Delta_T,0,\theta)}{\partial \theta}\left[\frac{\partial d_1}{\partial \Delta_1}\right] = -1/\left(6\theta\right)$. Together these two effects imply a *positive* impact of competition on the marginal benefit from innovation; and the business stealing effect, which simplifies to $\frac{\partial d_1(\Delta_T,0,\theta)}{\partial \theta}\left[\frac{\partial P_1}{\partial \Delta_1}\right] = \Delta_T/18 > 0$, accentuates this positive impact. Indeed, under targeted licensing, competition raises the innovator's marginal benefit from innovating, thereby increasing equilibrium innovation Δ_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 Δ_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 Δ_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 a 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 two sections.

4 Testing the Model: Data and Variables

To test our model, we develop a data set from five sources. The sources bring together data on innovation, competition, upstream-downstream relationships, and licensing deals.

4.1 IBISWorld Industry Linkages

First, to identify upstream and downstream industry relationship, we hand-collect data from 2008 IBISWorld reports. 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. Summary information is provided in Table 1, which 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).

[Insert Table 1 here.]

4.2 NBER Patent Citation Data

Next, we use the National Bureau of Economic Research (NBER) Patent Citation Database initially created by Hall *et al.* (2001, 2005) to measure innovation activity. This database contains annual information on patents and citations for publicly traded U.S. firms 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 first calculate the total number of patents firm i in industry j 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 industry j and year t,

$$CITATION\!-\!WEIGHTED\ PATENTS_{i,j,t} = PATENT\ COUNTS_{i,j,t} \cdot \frac{\sum_p PATENT\ CITATIONS_{i,j,p,t}}{\sum_i \sum_p PATENT\ CITATIONS_{i,j,p,t}},$$

where subscripts i, j, p, and t denote firm, industry, patent, and year, respectively; $PATENT\ COUNTS_{i,j,t}$ captures the total patent count for firm i in industry j in year t; and $PATENT\ CITATIONS_{i,j,p,t}$ represents the citations that patent p of firm i in industry j has received in year t.

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. Following Hall *et al.* (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: $TOTAL\ PATENT\ CITATIONS_{i,j,t}$, calculated as $\sum_p PATENT\ CITATIONS_{i,j,p,t}$; and $TOTAL\ CITATIONS\ PER\ PATENT_{i,j,t}$, computed as $\frac{\sum_p PATENT\ CITATIONS_{i,j,p,t}}{PATENT\ COUNTS_{i,j,t}}$.

4.3 Compustat Annual Industrial Data

Third, we collect financial data from Standard and Poor's Compustat Annual Files to compute downstream industry competition. 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.

We use the Compustat data to compute the Lerner index as a measure of the degree of industry competition. In particular, the market measure of competition is defined as $C_{j,t} = 1 - \frac{\sum_{i=1}^{n_{j,t}} L_{i,t}}{n_{j,t}}$, where j denotes the industry, i denotes a firm in the industry, and t is fiscal year. We follow Aghion *et al.* (2005) and compute the Lerner index as $L_{i,t} = \frac{Operating\ profit\ - Financial\ cost}{Sales}$, where operating profits net of depreciation provisions and an estimated financial cost of capital divided by sales measure the price cost margin. 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.

We also use the Text-based Network Industry Classifications (TNIC) developed by Hoberg and Philips (2010, 2016) to capture downstream industry competition in a way that is closer to the

"Hotelling" measure used in our model. Indeed, in our Hotelling model competition is captured by the degree of homogeneity between products $\theta = 1/t$, similar to the TNIC-based measure that is derived from computing firms' products similarities from the text analysis in their 10-K product descriptions. The TNIC do seem to provide a good fit for our theoretical measure of competition, and hence we perform our empirical analysis using TNIC-based industry competition as a robustness check.

We also use Compustat to compute a variety of firm and industry controls. 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, *R&D/ASSETS*, measured by R&D expenditures scaled by total assets; *LEVERAGE*, measured by total debt-to-total assets; investment in fixed assets, *CAPEX/ASSETS,* measured by capital expenditures scaled by total assets; growth opportunity; *MARKET-TO-BOOK*, measured by the firm's market-to-book ratio. To control for possible nonlinear effects of competition in the upstream market (Aghion *et al.*, 2005), we also include upstream product market competition (based on a Herfindahl index computed from annual sales) and its squared term in our baseline regressions. Detailed variable definitions are described in Table 2.

[Insert Table 2 here.]

4.4 SDC Strategic Alliance and Joint Venture Data

Fourth, we obtain data on firms' licensing strategies from the Joint Venture & Strategic Alliance database of Securities Data Company (SDC). We use SDC because 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.[19] 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, and cross licensing), the identities of licensors and licensees, the SIC codes of the participants and alliances, and so forth. Note that by definition exclusive and non-exclusive licensing strategies in the SDC database are analogous to the targeted licensing and market-wide licensing in our theoretical model, respectively. Despite some limitations to the SDC database, the information on licensing contract type, which is one of the main variables we use in our model, is quite accurate (Anand and Khanna, 2000). Specifically, by reading through the

[19]SDC reports a comprehensive coverage on the formation of all kinds of alliances by companies and the licensing deals among them all over the world from 1988. Given this, the licensing activities in SDC would be a good representative of our overall sample.

texts which describe the details about licensing deals, we hand-collect the data on whether a specific participant is a licensor or a licensee, whether it is a licensing contract based on market-wide strategy or targeted strategy, and 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.

4.5 Measuring Import Tariffs

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.

4.6 Summary Statistics

We present a summary statistics of the U.S. data in Table 3. 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.[20]In order to mitigate the impact of outliers, we winsorize all variables at the 1st and 99th percentiles.

[Insert Table 3 here.]

Table 3 presents means, medians, standard deviations, 10th and 90th percentiles for upstream firm innovation, downstream industry competition, and control variables. The patenting 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 Table 3 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.

[20]The sample for our baseline model is U.S. public traded firms across all industries over the period 1976-2006. We also do our empirical analysis by excluding financial and utility firms, and using the sample only from manufacturing industries as shown in Appendix A. We find that our main results are robust to samples with different industries.

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.

5 Main Findings

This section presents the main empirical findings in the paper. We begin by establishing a U-shaped relationship between upstream innovation and downstream competition in line with the predictions of the model. Then we discuss an instrumental variables strategy that allows us to assess the causal impact of changes in competition on changes in innovation. The final piece of our empirical analysis shows that licensing patterns vary with competition in a manner consistent with the model.

5.1 The Empirical Link between Competition and Innovation

We begin by estimating the following empirical relationship between downstream competition and upstream innovation:

$$\begin{aligned} CITATION-WEIGHTED\ PATENTS_{i,j,t} &= \beta_0 + \beta_1 \cdot DOWNSTREAM\ COMP_{j,t} + \\ &\beta_2 \cdot DOWNSTREAM\ COMP^2_{j,t} + \gamma \cdot Z_{i,t} + \delta_t + \alpha_j + \varepsilon_{i,j,t}, \qquad (17) \end{aligned}$$

where $CITATION-WEIGHTED\ PATENTS_{i,j,t}$ denotes the citation-weighted patent counts for firm i in industry j and year t, which captures upstream firm innovation level.[21] Our main explanatory variable of interest, downstream competition, 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.

$$DOWNSTREAM\ COMP_{j,t} = \frac{\sum_k DOWNSTREAM\ COMP_{j,k,t}}{n_{j,t}},$$

where $DOWNSTREAM\ COMP_{j,t}$ is the average of the downstream industry competition level that firms in upstream industy j face in year t; $DOWNSTREAM\ COMP_{j,k,t}$ 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 $Z_{i,t}$, δ_t,

[21] As a robustness exercise, in Appendix A we also present results based on citations per patent and total citations that firm i in industry j has in year t as proxies for upstream firm innovation.

and α_j as our control variables in the model specification. Among them, $Z_{i,t}$ is a vector of firm level and industry level characteristics; δ_t represents year fixed effects and controls for changes in the macroeconomic environment and systematic changes in patenting activities over time; and industry fixed effects α_j, based on five-digit NAICS industry dummies, control for any unobserved industry heterogeneity that is time invariant and affects firm patenting activities.

[Insert Table 4 here.]

Our main dependent variables are discrete and non-negative, and to account for this, in our baseline model we use a Negative Binomial model to investigate the impact of downstream industry competition on upstream firm innovation (Hashmi, 2013). We report our main empirical results in Table 4. Specifically, in column (1) of Panel A, the coefficient estimates on $DOWNSTREAM\ COMP$ and its squared term, $DOWNSTREAM\ COMP^2$, are -8.541 and 6.659, and which are significant at the 5% and 1% levels respectively. The effects are economically large. Because the derivative of innovation with respect to downstream competition from Equation (17) is $\beta_1 + 2\beta_2 C_{j,t}$, the negative sign for β_1 and positive sign for β_2 clearly support for a U-shaped relationship between downstream competition and upstream innovation.

In column (2) of Panel A, we 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 upstream competition and its square to control for the impact of upstream industry competition on upstream firm innovation. We control for year and industry fixed effects as well. The results in column (2) show that the coefficient estimates on $DOWNSTREAM\ COMP$ and $DOWNSTREAM\ COMP^2$ remain significantly negative and positive respectively. This again provides support for the U-shaped relationship between downstream competition and upstream innovation.

In columns (3) – (7), we consider two alternative models, OLS and Poisson model, respectively. In particular, in columns (3) – (5) 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. Specifically, column (3) shows the results of the impact of downstream competition on upstream innovation. The coefficients of $DOWNSTREAM\ COMP$ and $DOWNSTREAM\ COMP^2$ are -3.334 and 1.983 respectively, and both are significant at the 5% level. Columns (4) and (5) add firm and industry characteristics, year fixed effects, and industry fixed effects. The coefficients of $DOWNSTREAM\ COMP$ and $DOWNSTREAM\ COMP^2$ remain significantly negative and positive respectively.

In columns (6) and(7), we present the results of the effect of downstream competition on upstream innovation in a Poisson regression. As shown in column (6), the coefficient estimates on $DOWNSTREAM\ COMP$ and $DOWNSTREAM\ COMP^2$ are -3.241 and 2.680, and both are significant at the 10% and 5% levels, respectively. Firm and industry level controls are added into the model specification in column (7). The coefficients of $DOWNSTREAM\ COMP$ and $DOWNSTREAM\ COMP^2$ remain significantly negative and positive respectively. These results provide consistent support for the U-shaped relationship between downstream competition and upstream innovation when estimating based on the Poisson model, and controlling for firm and industry characteristics, year and industry fixed effects.

As a robustness check, we use the Text-based Network Industry Classifications (TNIC) of Hoberg and Philips (2016) as an alternative industry classification system. The TNIC are obtained by computing firm pairwise similarity scores from text analysis in firms' 10-K product descriptions. The similarities-based TNIC provide a good fit to our theoretical model, where competition is captured by the degree of homogeneity between products. Specifically, Hoberg and Philips (2010, 2016) develop the FIC industry classification which is based on an algorithm clustering firms together to maximize within-industry similarity. In their dataset, they include FIC-500, FIC-400, FIC-300, FIC-200, FIC-100, FIC-50 and FIC-25 industries to represent 500, 400, 300, 200, 100, 50, 25 different industry groups respectively. Following Hoberg, Phillips, and Prabhala (2014), we use FIC-300 industries to compute the TNIC-based HHI index for each downstream industry.[22] Consistent with our baseline model in Table 4, we adopt a Negative Binomial model for the analysis, and control for R&D expenditure, leverage ratio, market-to-book value, return on asset, capital expenditure, upstream industry competition and its square term, which may affect firms' innovative activities. We also include year fixed effects and industry fixed effects into the specification. All standard errors are adjusted for within-firm clustering.

[Insert Table 5 here.]

The results are presented in Table 5. As shown in column (1), the coefficient estimates on $DOWNSTREAM\ COMP(TNIC)$, a TNIC-based downstream industry competition measure, and

[22] We also try FIC-500, FIC-400, FIC-200, FIC-100 and find that our results are robust to these different industry groups.

its square term, $DOWNSTREAM\ COMP(TNIC)^2$, are -4.027 and 6.023 respectively, and both are significant at the 5% level. In column (2), we include the following control variables into the model specification: R&D expenditure, leverage ratio, market-to-book value, return on asset, capital expenditure, upstream industry competition and its square term. We obtain significant results similar to those presented in column (1). We further control for year fixed effects and industry fixed effects in column (3). The coefficient estimates on both TNIC-based downstream competition and its square term remain significant at the 1% or 5% level, depending on the specification and variable. In all, the results presented in Table 5 suggest that the U-shaped relationship between downstream competition and upstream innovation still holds when using the TNIC-based industry competition measure.

We also consider a number of additional robustness checks. In particular, to address the concern that a significant coefficient on the square term of downstream competition is necessary but insufficient to establish a quadratic U-shaped relationship, we 1) verify that the threshold level of competition at which innovation is minimized is indeed within the range of values for downstream industry competition; and 2) split our data sample into different percentiles to verify that the impact of downstream competition on upstream innovation is negative at low levels of competition and positive at high levels of competition. These and other robustness checks yield results that are consistent with our baseline results, and are discussed in more detail in Appendix A.

5.2 Does Competition Cause Innovation?

One potential concern in the analysis presented above relates to the endogeneity of downstream industry competition. In general, some omitted factor like expected industry profitability or market size might jointly affect downstream industry structure and upstream firm innovation.

To address the potential endogeneity of downstream industry competition, we use an instrumental variable strategy designed to isolate exogenous changes to downstream industry competition by exploiting changes in tariffs. 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 in 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) and 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 data 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. We then 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 a competitive shock for each downstream industry as a dummy variable, $IMPORT\ TARIFF\ CHANGE_{k,t}$, which equals one if the largest tariff rate reduction in downstream industry k by year 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 we identified, we take the average of competitive shocks coming from the downstream industries associated with a specific upstream industry j. We then get the average of downstream industry competition for the upstream industry j in year t, i.e., $IMPORT\ TARIFF\ CHANGE_{j,t} = \frac{\sum_k IMPORT\ TARIFF\ CHANGE_{k,t}}{n_{j,t}}$, where $n_{j,t}$ is the number of downstream industries related to the upstream industry j in year t.

[Insert Table 6 here.]

Table 6 presents the estimation results. Column (1) presents the result of the first stage. In particular, we regress downstream competition on the competitive shock, controlling for R&D expenditure, firm leverage, market-to-book ratio, ROA, capital expenditure, and upstream industry competition and its square term. We also control for year fixed effects and industry fixed effects in the estimation. As shown in column (1), the coefficient of $IMPORT\ TARIFF\ CHANGE$ has a value of 0.02, and is positive and significant at the 1% level. And the F-value is 431.7, well above the conventional level of 10 advocated by Stock and Yogo (2005). These suggest that reductions in import tariff rate as the instrument is correlated with the endogenous explanatory variable, downstream competition, and we have a strong first stage.

Because we only have a single instrument but we wish to capture a quadratic relationship in the data, we split our sample into two subsamples by using the threshold point of the U-shaped relationship. This threshold point determined analytically by applying the regression estimates from

[23] We also try two alternatives in Appendix A, 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. Our results are robust to different definitions of competitive shock.

Table 4 into the formula for the derivative of innovation with respect to downstream competition, setting this derivative to zero and solving for the threshold degree of competition. Having determined the threshold, we then use the predicted value from the first stage regression as the instrumented regressor in each sub-sample regression. Columns (2) - (4) report the result of the second stage using the subsample below the threshold point of downstream competition. Specifically, in column (2), we regress upstream innovation on the predicted value of downstream competition from the first stage, controlling for R&D expenditure, firm leverage, market-to-book ratio, ROA, capital expenditure, and upstream industry competition and its square term. Column (2) shows that the coefficient estimate on $DOWNSTREAM\ COMP$(Fitted) is negative and significant at the 1% level, suggesting that downstream competition has a negative relationship with upstream innovation. In columns (3) and (4), we further control for year fixed effects and industry fixed effects, respectively. The coefficient of $DOWNSTREAM\ COMP$(Fitted) remains negative and significant - at the 5% and 10% levels, respectively - in these two columns. These provide empirical support for the left hand side of the U-shaped relationship. In other words, when downstream competition is below a threshold point, upstream innovation is decreasing in downstream industry competition.

Columns (5) - (7) show the results of the second stage using the subsample above the threshold point of downstream competition. Column (5) shows that the effect of downstream competition on upstream innovation is positive and significant at the 1% level, after controlling for R&D expenditure, firm leverage, market-to-book ratio, ROA, capital expenditure, and upstream industry competition and its square term. We add year fixed effects and industry fixed effects in columns (6) and (7), respectively, and find that the impact of downstream competition on upstream innovation remains significantly positive - at the 5% and 10% levels, respectively - in these two columns. These indicate that upstream innovation is increasing in downstream competition when downstream competition is above a threshold point. i.e., the right hand side of the U-shaped relationship is supported by our empirical evidence as well.

[Insert Table 7 here.]

As an additional robustness check, we split the sample at the median level of industry concentration and repeat our split-sample IV strategy. These results are presented in Table 7, and are qualitatively similar to those presented in Table 6.

5.3 Exploring the Licensing Channel

While the above results show that downstream industry competition has a U-shaped impact on upstream firm innovation, they are silent on whether licensing considerations are central to this relationship. In this section, we investigate the role that upstream firms' licensing strategies play.

Two licensing-related empirical implications emerge from our theoretical model. First, downstream competition has a negative impact on upstream innovation under market-wide licensing and a positive impact on upstream innovation under targeted licensing. And second, competition increases the appeal of targeted licensing relative to market-wide licensing.

To investigate these conjectures, we use the licensing deal data from the Strategic Alliance database of Securities Data Company (SDC), which we described above in Section 4. Because SDC focuses more on U.S. firms, and because the deal sample prior to 1990 is incomplete, we restrict our analysis to the licensing deals between public U.S. firms from $1990-2006$. We start 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. Merging Compustat and SDC data give us a sample with 1,415 firm-year observations. Our final step of data collection is to link the merged dataset with the NBER Patent Citation Dataset, obtaining firms' information on patenting since January 1, 1990. This gives us a final sample of 605 observations, with 631 licensors and licensees traded in United States. Typically, within an industry, the number of licensors varies from 1 to 50, with a median of 4. Therefore, we add upstream industry concentration in our regressions to control for the impact of upstream competitors on the upstream firm's innovation.

To examine the first conjecture, we consider the impact of downstream competition and licensing strategy on upstream innovation. Panel A of Table 8 presents the results. Specifically, for the same reasons as in the baseline model, we again employ a Negative Binomial model here. The dependent variable is $CITATION-WEIGHTED\ PATENTS$. The independent variables are $DOWNSTREAM\ COMP$, representing downstream industry competition level; $LICENSE\ TARGETED$, a dummy setting to 1 if targeted licensing is used, and zero otherwise; and an interaction of $DOWNSTREAM\ COMP$ and $LICENSE\ TARGETED$. We also include a vector of firm level and industry level characteristics that may impact a firm's future innovation productivity, i.e., R&D expenditure, leverage ratio, market-to-book value, return on asset, capital expenditure, upstream industry competition and its square term. As well, we include year fixed effects, to control for the impact of some variables that change over time, and industry fixed effects, to control for time-invariant industry differences.

The results presented in Panel A of Table 8 are consistent with the predictions of our model. In particular, as shown in column (1), the coefficient estimate on $DOWNSTREAM\ COMP$ is negative with a value of 8.654, and significant at the 1% level, suggesting that downstream competition has a negative impact on upstream innovation under market-wide licensing. Moreover, the coefficient estimate on the interaction term is positive with a value of 12.097, and significant at the 1% level. Thus, under targeted licensing downstream competition has a positive impact on upstream innovation ($12.097 - 8.654 = 3.443 > 0$). We add a vector of firm level and industry level characteristics in the model specification in column (2), and get similar results to those presented in column (1). In column (3), we further control for year fixed effects and industry fixed effects. The coefficient estimates on $DOWNSTREAM\ COMP$ and the interaction term remain significantly negative and positive, respectively. In sum, the results presented in Panel A of Table 8 provide support for the first conjecture, namely that downstream competition has a negative impact on upstream innovation under market-wide licensing and a positive impact on upstream innovation under targeted licensing.

[Insert Table 8 here.]

To examine the second conjecture, we empirically consider how downstream industry competition impacts the appeal of targeted licensing relative to market-wide licensing. Panel B of Table 8 presents the results regarding the impact of downstream competition on upstream firms' licensing choices. In particular, we look at how the propensity to apply a targeted licensing strategy is determined by the product market competition level in the downstream industries. The dependent variable is $LICENSE\ TARGETED$, and the independent variable is $DOWNSTREAM\ COMP$. We also include a vector of firm level and industry level characteristics, which may affect the choice of licensing strategies, into our model specification (Anand and Khanna, 2000; Kim and Vonortas, 2006; and Somaya, Kim, and Vonortas, 2010). Specifically, we control for firm level characteristics such as firm size, prior license (a proxy for whether a focal firm issued licenses before or not), knowledge stock, and complexity (a proxy for the complexity of technology); and for industry level characteristics such as industry concentration, industry growth, and IPR strength. We also control for year fixed effects and industry fixed effects. All standard errors are adjusted for within-firm clustering. As shown in column (1), the coefficient estimate on $DOWNSTREAM\ COMP$ is positive and significant at the 1% level, suggesting that downstream industry competition increases the appeal of targeted licensing relative to market-wide licensing. In columns (2) and (3), we include firm and industry level characteristics, and year and industry fixed effects, respectively. All of the coefficient estimates on $DOWNSTREAM\ COMP$ remain positive and significant. In all, consistent with the second conjecture, the results presented in Panel B of Table 8 suggest that competition increases the appeal of targeted licensing over market-wide licensing.

6 Conclusion

This paper develops a model in which technology markets mediate the effects of downstream competition and upstream innovation. When an upstream innovator can choose between a targeted licensing strategy to one downstream competitor or a market-wide licensing strategy to both competitors simultaneously, we characterize an equilibrium threshold level of competition below which market-wide licensing is optimal and innovation is decreasing in competition, and above which targeted licensing is optimal and innovation is increasing in competition. When we take the model to the data we find clear evidence of a U-shaped relation between downstream competition and upstream innovation. Licensing patterns are a key mechanism behind this relation.

Our analysis suggests several directions for future research. In order to provide clear, stark and tractable results, we make strong assumptions and develop a stylized model. In this context, it is natural to question 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 Appendix C, we discuss what would happen in auction and two-part tariff contexts, and show that the results are very similar to those of the main model.

Another natural question 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 through the licensing payoffs received by the innovator. 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. Although a

Hotelling demand framework provides simplicity, we believe that the intuition behind our main results are quite general. Our conjecture is 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 under the demand specifications just enumerated is a natural and appealing extension of this model, and one which we look forward to examining in future research.

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Table 1: Sample Distribution Across Industry

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 customer industries (defined at the five-digit NAICS level).

NAICS code	Industry group name	Firm-years	% of Sample	# Downstream Ind.
11	Agriculture, Forestry, Fishing and Hunting	57	0.23	80
21	Mining	577	2.31	42
22	Utilities	189	0.76	16
23	Construction	66	0.26	63
31	Manufacturing I	777	3.11	78
32	Manufacturing II	5925	23.71	191
33	Manufacturing III	13677	54.74	226
42	Wholesale Trade	203	0.81	231
44	Retail Trade I	37	0.15	41
45	Retail Trade II	15	0.06	47
48	Transportation and Warehousing I	150	0.60	68
49	Transportation and Warehousing II	5	0.02	25
51	Information	1357	5.43	54
52	Finance and Insurance	488	1.95	45
53	Real Estate and Rental and Leasing	258	1.03	48
54	Professional, Scientific and Technical Services	819	3.28	92
56	Administration, Business Support & Waste Management Services	162	0.65	69
61	Educational Services	22	0.09	21
62	Healthcare and Social Assistance	143	0.57	37
71	Arts, Entertainment and Recreation	4	0.02	22
72	Accommodation and Food Services	56	0.22	8
Total		24,987	100.00	

Table 2: Variable Definitions

This table reports summary statistics for variables constructed using a sample of U.S. public firms from 1976-2006. All variables are measured annually at the firm level or industry level.

CITATION-WEIGHTED PATENTS	The number of patents a firm receives in a given year weighted by the citations of these patents.
TOTAL PATENT CITATIONS	The total citations in a given year to patents that a firm has.
TOTAL CITATIONS PER PATENT	The total citations in a given year, divided by that year's total number of patents.
DOWNSTREAM COMP	One minus the Lerner index for a downstream industry.
DOWNSTREAM COMP (TNIC)	One minus the HHI index for a downstream industry based on FIC-300 TNIC
R&D / ASSETS	The ratio of Compustat research and development expenditures to the book value of total assets, measured at the end of the fiscal year.
LEVERAGE	Book value of debt divided by book value of total assets measured at the end of fiscal year
MARKET-TO-BOOK	Market value of equity plus book value of assets minus book value of equity minus balance sheet deferred taxes divided by book value of assets.
ROA	Operating income before depreciation divided by book value of total assets, measured at the end of fiscal year
CAPEX/ASSETS	Capital expenditures scaled by book value of total assets measured at the end of fiscal year t.
UPSTREAM COMP	One minus the Herfindahl index of four-digit SIC industry j to which firm i belongs, measured at the end of fiscal year t.
LICENSE TARGETED	A dummy variable setting to 1 if targeted licensing strategy is adopted, and 0 if market-wide licensing is used.
FIRM SIZE	Log of firm sales amount in a given year.
PRIOR LICENSE	A dummy variable setting to 1 if a licensor firm had sold licenses up to period t-1, and 0 otherwise.
KNOWLEDGE STOCK	The number of patents granted to the firm in year t, plus the number of patents granted to the firm up to year t-1, depreciated by 15%.
COMPLEXITY	A dummy variabel setting to 1 if the two-digit SIC industry that a firm operates in is equal to or above 35, and 0 otherwise.
INDUSTRY CONCENTRATION	One minus the Lerner index based on four-digit SIC industries.
INDUSTRY GROWTH	The percentage change in total sales in four-digit SIC industries.
IPR STRENGTH	Proxied by industry patent intensity, measured by industry patents divided by industry R&D expenditure in a given year.

Table 3: Summary Statistics

This table reports summary statistics for variables constructed using a sample of U.S. public firms from 1976-2006. All variables are measured annually at the firm level or industry level. Variable definitions are provided in Table 2.

VARIABLES	10% Pctile.	Mean	Median	90% Pctile.	Std. Dev.	Obs.
CITATION-WEIGHTED PATENTS	0.000	0.1362	0.002	0.059	0.777	24,845
TOTAL PATENT CITATIONS	1.046	423.6158	37.990	629.598	2335.598	24,915
TOTAL CITATIONS PER PATENT	0.620	15.548	10.485	33.178	20.456	24,915
DOWNSTREAM COMP	0.682	0.7687	0.779	0.844	0.071	24,915
R&D/ASSETS	0.009	0.1081	0.052	0.251	0.168	20,780
LEVERAGE	0.000	0.2154	0.186	0.450	0.202	24,785
MARKET-TO-BOOK	0.888	2.257	1.458	4.242	2.372	21,498
ROA	-0.238	0.0442	0.121	0.240	0.292	24,697
CAPEX/ASSETS	0.016	0.0632	0.050	0.124	0.051	24,378
UPSTREAM COMP	0.601	0.848	0.926	0.987	0.190	24,914

Table 4: Downstream Competition and Upstream Innovation

This table presents coefficients estimates of regressions which examine the effect of downstream industry competition on upstream firm innovation (equ. (17)). The dependent variable is CITATION-WEIGHTED PATENTS for firm i in industry j and year t. Column (1) presents the results with year and industry fixed effects by using negative binomial method, and column (2) further includes firm level and industry level controls. Column (3) presents the results by using OLS, and columns (4) and (5) based on OLS include year and industry fixed effects, and control for firm characteristics respectively. Finally, columns (6) and (7) show the results by using poisson model with year and industry fixed effects and firm and industry level controls. The sample period is from 1976-2006. All variables are defined in Table 2. The t-statistics reported in parentheses below the coefficient estimates are based on standard errors adjusted for within-firm clustering. Significance at the 10%, 5%, and 1% level is indicated by *, **, ***, respectively.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DOWNSTREAM COMP	-8.541**	-7.001*	-3.334**	-3.796**	-1.500*	-3.241*	-5.287*
	(3.674)	(3.953)	(1.326)	(1.510)	(0.908)	(1.806)	(2.861)
DOWNSTREAM COMP^2	6.659***	5.677**	1.983**	2.237**	1.004*	2.680**	4.22**
	(2.532)	(2.760)	(0.830)	(0.930)	(0.556)	(1.390)	(2.160)
R & D / ASSETS		-11.137***		-0.086*	-0.139*		-10.445***
		(2.746)		(0.050)	(0.070)		(3.513)
LEVERAGE		0.203		0.010	0.063*		0.257
		(0.538)		(0.026)	(0.032)		(0.481)
MARKET-TO-BOOK		-0.240***		-0.004***	-0.004***		-0.207***
		(0.077)		(0.001)	(0.001)		(0.065)
ROA		3.404***		0.024	0.030		2.073***
		(0.613)		(0.025)	(0.025)		(0.753)
CAPEX/ASSETS		3.995**		0.155	0.096		1.785
		(1.982)		(0.147)	(0.155)		(1.800)
UPSTREAM COMP		-3.358*		0.326*	-0.134		-2.565
		(1.972)		(0.188)	(0.100)		(2.202)
UPSTREAM COMP^2		2.316		-0.247	(0.069)		1.515
		(1.578)		(0.165)	(0.103)		(1.815)
Fixed Effects:							
Year	Yes	Yes	No	No	Yes	Yes	Yes
Industry	Yes	Yes	No	No	Yes	Yes	Yes
Method	NB	NB	OLS	OLS	OLS	Poisson	Poisson
Clusters	3,718	2,716	3,718	2,716	2,716	3,718	2,716
Observations	24,845	17,743	24,845	17,743	17,743	24,845	17,743

Table 5: Innovation and Downstream Competition with Alternative Industry

The dependent variable in each specification is CITATION-WEIGHTED PATENTS for firm i in industry j and year t. Industry classifications are based on Hoberg and Phillips (2010, 2016) text-based industry classifications, which form industries based on text analysis of 10-K reports. All variables are defined in Table 2. The t-statistics reported in parentheses below the coefficient estimates are based on standard errors adjusted for within-firm clustering. Significance at the 10%, 5%, and 1% level is indicated by *, **, ***, respectively.

VARIABLES	(1)	(2)	(3)
DOWNSTREAM COMP (TNIC)	-4.027**	-5.166***	-5.444***
	(1.590)	(1.974)	(2.005)
DOWNSTREAM COMP(TNIC)^2	6.023**	7.331**	7.640***
	(2.524)	(3.161)	(3.211)
R&D/ASSETS		-4.549***	-4.436***
		(1.299)	(1.257)
LEVERAGE		0.679**	0.708**
		(0.333)	(0.326)
MARKET-TO-BOOK		-0.0846**	-0.0827**
		(0.039)	(0.038)
ROA		3.601***	3.592***
		(0.475)	(0.480)
CAPEX/ASSETS		1.187	1.149
		(1.395)	(1.411)
UPSTREAM COMP			-2.179
			(1.561)
UPSTREAM COMP^2			1.350
			(1.471)
Year fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Clusters	2349	1800	1800
Observations	9448	7140	7140

Table 6: Split-sample IV Regressions: Imputed Splits

This table reports instrumental variables regressions of upstream innovation on downstream competition. The first stage, reported in column (1), is an OLS regression of downstream competition on the RHS variables reported in the table. In this specification, the instrument is the change in tariff rates in the industry, based on data obtained from Schott (2010). We first compute for each industry the median tariff rate change as well as the largest tariff rates changes. Then we define for each downstream industry the dummy variable, $IMPORT\ TARIFF\ CHANGE_{k,t}$, 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. Then we average the competitive shocks coming from the downstream industries associated with an upstream industry. Then we split the sample according to whether the industry in question is above or below the peak implied by the linear and quadratic terms in Column (5) of Table 4. In columns (2)-(4), we regress upstream innovation on downstream competition for below-peak levels of industry competition, using the generated regressor from the first stage as an instrument for downstream competition. Columns (5)-(7) repeat the same analysis but focus on the set of industries with above-peak competition each year. The sample period is from 1976-2006. All variables are defined in Table 2. The t-statistics reported in parentheses below the coefficient estimates are based on standard errors adjusted for within-firm clustering. Significance at the 10%, 5%, and 1% level is indicated by *, **, ***, respectively.

	First Stage	2^{nd} Stage-Below Cut			2^{nd} Stage-Above Cut		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DOWNSTREAM COMP(Fitted)		-24.91***	-30.73**	-64.75*	9.97***	18.36**	21.08*
		(9.379)	(12.492)	(36.160)	(3.218)	(7.694)	(11.440)
IMPORT TARIFF CHANGE	0.02***						
	(0.002)						
R&D/ASSETS	-0.01	5.51	6.71	13.21***	-9.87**	-10.79***	-16.54***
	(0.010)	(4.384)	(4.507)	(4.219)	(4.253)	(4.106)	(4.579)
LEVERAGE	-0.00	-2.67*	-3.11**	-5.73***	-1.39	-1.41	0.13
	(0.004)	(1.388)	(1.450)	(1.611)	(1.201)	(1.183)	(1.212)
MARKET-TO-BOOK	0.00**	0.07	0.12	0.17	-0.39***	-0.40***	-0.43***
	(0.001)	(0.297)	(0.245)	(0.280)	(0.110)	(0.111)	(0.139)
ROA	0.00	9.94***	9.56***	12.74***	1.06	1.21	2.60**
	(0.004)	(1.874)	(1.943)	(1.943)	(1.325)	(1.456)	(1.220)
CAPX/ASSETS	0.00	17.31***	17.87***	3.00	10.22***	11.25***	12.24***
	(0.016)	(5.189)	(5.865)	(8.546)	(3.883)	(4.072)	(3.823)
UPSTREAM COMP	-0.04	5.21	5.06	-1.56	3.55	5.88	1.14
	(0.032)	(5.452)	(5.118)	(7.867)	(3.514)	(3.947)	(4.149)
UPSTREAM COMP^2	0.06**	-6.32	-5.90	-4.30	-2.51	-4.89	-3.04
	(0.025)	(5.349)	(4.812)	(7.340)	(2.676)	(3.059)	(3.538)
Year Fixed Effects	Yes	No	Yes	Yes	No	Yes	Yes
Industry Fixed Effects	Yes	No	No	Yes	No	No	Yes
Obs.	3,620	530	530	530	3,090	3,090	3,090
R^2	0.537	0.282	0.316	0.459	0.0538	0.0622	0.205
F-test	431.7						

Table 7: Split-sample IV Regressions: Median Splits

This table reports instrumental variables regressions of upstream innovation on downstream competition. The first stage, reported in column (1), is an OLS regression of downstream competition on the RHS variables reported in the table. In this specification, the instrument is the change in tariff rates in the industry, based on data obtained from Schott (2010). We first compute for each industry the median tariff rate change as well as the largest tariff rates changes. Then we define for each downstream industry the dummy variable, $IMPORT\ TARIFF\ CHANGE_{k,t}$, 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. Then we average the competitive shocks coming from the downstream industries associated with an upstream industry. Then we split the sample according to whether the industry in question is above or below the median industry concentration each year. In columns (2)-(4), we regress upstream innovation on downstream competition for below-median levels of industry competition, using the generated regressor from the first stage as an instrument for downstream competition. Columns (5)-(7) repeat the same analysis but focus on the set of industries with above-median competition each year. The sample period is from 1976-2006. All variables are defined in Table 2. The t-statistics reported in parentheses below the coefficient estimates are based on standard errors adjusted for within-firm clustering. Significance at the 10%, 5%, and 1% level is indicated by *, **, ***, respectively.

	First Stage	2^{nd} Stage-Below Cut			2^{nd} Stage-Above Cut		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DOWNSTREAM COMP (Fitted)		-0.61	-23.11***	-39.49***	18.39***	13.64***	23.56*
		(6.294)	(6.328)	(9.694)	(3.862)	(2.915)	(13.624)
IMPORT TARIFF CHANGE	0.02***						
	(0.002)						
R&D/ASSETS	-0.01	-5.74	-15.93***	-17.87***	-8.13**	-12.77***	-13.35***
	(0.010)	(4.060)	(4.660)	(4.740)	(4.033)	(4.549)	(4.530)
LEVERAGE	-0.00	-1.44	0.02	-0.09	-2.55*	-1.04	-1.20
	(0.004)	(1.847)	(1.460)	(1.429)	(1.526)	(1.489)	(1.454)
MARKET-TO-BOOK	0.00**	-0.33**	-0.29*	-0.33**	-0.46***	-0.47***	-0.48***
	(0.001)	(0.139)	(0.152)	(0.165)	(0.120)	(0.135)	(0.152)
ROA	0.00	1.55	2.92*	4.14***	2.38**	2.48**	3.64***
	(0.004)	(1.479)	(1.639)	(1.581)	(1.200)	(1.155)	(1.241)
CAPEX/ASSETS	0.00	2.46	4.30	7.47*	13.75***	13.41***	14.24***
	(0.016)	(4.688)	(3.763)	(4.052)	(4.150)	(3.945)	(4.258)
UPSTREAM COMP	-0.04	2.46	-0.48	-3.11	26.58	2.61	3.03
	(0.032)	(3.358)	(4.454)	(5.289)	(19.772)	(4.664)	(4.801)
UPSTREAM COMP^2	0.06**	-2.15	-1.11	1.63	-17.44	-2.45	-3.54
	(0.025)	(2.879)	(3.549)	(4.463)	(12.856)	(3.657)	(3.855)
	0.80***	-0.71	10.29**	21.62***	-25.16***	-28.82	-38.56
	(0.012)	(5.018)	(5.222)	(7.117)	(8.311)	(.)	(.)
Year Fixed Effects	Yes	No	Yes	Yes	No	Yes	Yes
Industry Fixed Effects	Yes	No	No	Yes	No	No	Yes
Observations	3,620	1,733	1,733	1,733	1,887	1,887	1,887
R^2	0.537	0.0243	0.244	0.259	0.0872	0.188	0.198
F-test	431.7						

Table 8: Downstream Competition, Licensing, and Innovation

This table captures the interaction between downstream competition, licensing, and innovation. In Panel A, the dependent variable is CITATION-WEIGHTED PATENTS for firm i in industry j and year t. And the dependent variable in Panel B is LICENSE TARGETED. All variables are defined in Table 2. The t-statistics reported in parentheses below the coefficient estimates are based on standard errors adjusted for within-firm clustering. Significance at the 10%, 5%, and 1% level is indicated by *, **, ***, respectively.

Panel A

VARIABLES	(1)	(2)	(3)
DOWNSTREAM COMP	-8.654***	-6.345**	-2.083*
	(2.354)	(1.443)	(1.240)
LICENSE TARGETED	-13.372***	-11.439***	-5.001**
	(3.812)	(3.607)	(2.453)
DOWNSTREAM COMP*	12.097**	10.208***	4.944*
LICENSE TARGETED	(3.923)	(3.780)	(2.652)
LEVERAGE		5.155*	2.824*
		(2.977)	(1.573)
MARKET-TO-BOOK		-1.091***	-0.612***
		(0.158)	(0.171)
ROA		9.587***	8.115***
		(1.360)	(1.495)
CAPEX/ASSETS		-6.875	-5.034
		(4.582)	(3.681)
UPSTREAM COMP		13.273	-23.081*
		(10.052)	(12.827)
UPSTREAM COMP^2		-8.595	13.423
		(7.500)	(9.033)
Year fixed effects	No	No	Yes
Industry fixed effects	No	No	Yes
Observations	567	472	472

Panel B

VARIABLES	(1)	(2)	(3)
DOWNSTREAM COMP	0.523***	0.348**	0.253*
	(0.114)	(0138)	(0.145)
FIRM SIZE		0.002	0.007
		(0.007)	(0.010)
PRIOR LICENSE		-0.053*	-0.022
		(0.030)	(0.040)
KNOWLEGE STOCK		-0.001*	-0.001*
		(0.000)	(0.000)
COMPLEXITY		-0.162**	0.089
		(0.042)	(0.121)
INDUSTRY CONCENTRATION		-0.029**	-0.015
		(0.012)	(0.018)
INDUSTRY GROWTH		0.039	-0.022
		(0.093)	(0.095)
IPR STRENGTH		0.072	0.093
		(0.047)	(0.125)
Year fixed effects	No	No	Yes
Industry fixed effects	No	No	Yes
Observations	583	567	567

A Appendix: Empirical Robustness

This appendix discusses four robustness checks performed on the main empirical tests in the paper. *The regression results and associated tables discussed below are suppressed for brevity, but are available from the authors upon request.*

First, 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 *et al.*, 2016), we perform 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 4 in our baseline model as an example, the turning point of the U-shaped relationship is $0.6165(7.001/(2*5.677) = 0.6165)$, which is clearly within our data range. (2) We 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. (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.

Second, 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 *et al.*, 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 apply three different models in our regression: Negative Binomial, OLS, and Poisson models. Both in the case of citations per patent and in the case of total patent citations, our results provide support for a U-shaped relationship between downstream competition and upstream innovation.

Third, 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 again run negative binomial, poisson and OLS regression models, and as in the baseline model, the U-shaped relationship between downstream competition and upstream innovation is highly significant.

Fourth, our finding of a 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, using negative binomial, Poisson and OLS regression models.

Finally, in Section 5.2 we define a competitive shock for a downstream industry by whether the largest tariff rate reduction in the downstream industry is three times larger than the median tariff rate reduction in that industry. Alternatively, we also try two other definitions of the competitive shock for a downstream industry. Specifically, we define 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. Our results are robust to these two different definitions of competitive shock.

Overall, the results provide support for a U-shaped relationship between competition and innovation.

B Appendix: Proofs

B.1 Proof of Lemma 1

Using (4), we can express (7) as follows:

$$\begin{aligned} -2\left[-\frac{1}{3}\left(\frac{1}{2}-\frac{\Delta_M^*\theta}{6}\right)-\frac{\theta}{6}\left(\frac{1}{\theta}-\frac{\Delta_M^*}{3}\right)\right] &= \Delta_M^*;\text{ or} \\ \frac{2}{3}-\frac{2\Delta_M^*\theta}{9} &= \Delta_M^*; \end{aligned}$$

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 Δ_M^*, the smallest expected demand and price-cost margin a Firm i can expect to obtain (in the no-access case) simplify to $d_i = \frac{1}{2} - \frac{\Delta_M^*\theta}{6} = \frac{1}{2} - \frac{\theta}{(9+2\theta)}$ and $P_i = \frac{1}{\theta} - \frac{\Delta_M^*}{3} = \frac{1}{\theta} - \frac{2}{(9+2\theta)}$, respectively; which are both strictly positive for all $\theta \in \Theta$.

Using (4) and substituting $\Delta_M^* = 6/(9+2\theta)$ into expressions (5) and (6), we obtain $z_{1M} = z_{2M} = \frac{2(9+\theta)}{(9+2\theta)^2}$ and $Z_M^* = \frac{2}{(9+2\theta)} - h$, respectively. □

B.2 Proof of Lemma 2

Using (4), we can express (10) as follows:

$$\begin{aligned} \frac{1}{3}\left(\frac{1}{2}+\frac{\Delta_T^*\theta}{6}\right)+\frac{\theta}{6}\left(\frac{1}{\theta}+\frac{\Delta_T^*}{3}\right) &= \Delta_T^*;\text{ or} \\ \frac{1}{3}+\frac{\Delta_T^*\theta}{9} &= \Delta_T^*; \end{aligned}$$

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 Δ_T^*, the smallest expected demand and price-cost margin a Firm i can expect to obtain (in the no-access case) simplify to $d_i = \frac{1}{2} - \frac{\Delta_T^*\theta}{6} = \frac{1}{2} - \frac{\theta}{2(9-\theta)}$ and $P_i = \frac{1}{\theta} - \frac{\Delta_T^*}{3} = \frac{1}{\theta} - \frac{1}{(9-\theta)}$, respectively; which are both strictly positive for all $\theta \in \Theta$.

Using (4) and substituting $\Delta_T^* = 3/(9-\theta)$ into expressions (8) and (9), we obtain $z_{1T}^* = \frac{18-\theta}{2(9-\theta)^2}$, and $Z_T^* = \frac{1}{18-2\theta}$, respectively. □

B.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 $\theta \in \Theta$.

To see that $\partial\theta^*(h)/\partial h < 0$, note that $\theta^*(h)$ is the value of θ 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 $\frac{\partial\theta^*}{\partial h} = -\frac{\partial A/\partial h}{\partial A/\partial\theta^*} < 0$. □

C Appendix: Model Extensions

C.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[24] over targeted licensing iff $Z_M^* \geq Z_T^*$, iff:

$$\sum_{i=1}^{2} z_{iM}(\Delta_M, \theta) - K_M(\Delta_M) > z_{1T}(\Delta_T, \theta) - K_T(\Delta_T). \tag{18}$$

Re-writing expression (18) in the following way helps highlight the three key factors affecting the tradeoff between market-wide licensing and targeted licensing:

$$\begin{aligned} &[z_{2M}(\Delta_M, \theta)] \\ &- [(z_{1T}(\Delta_M, \theta) - K_T(\Delta_M)) - z_{1M}(\Delta_M, \theta) - K_M(\Delta_M)] \\ &- [(z_{1T}(\Delta_T, \theta) - K_T(\Delta_T)) - (z_{1T}(\Delta_M, \theta) - K_T(\Delta_M))] > 0. \end{aligned} \tag{19}$$

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 Δ_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 symmetric profits for Firm 1 under market-wide licensing is smaller than the leader 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 Δ_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 Δ_T and reduces Δ_M; thus *competition increases the innovation disadvantage*. This is another

[24] 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.

[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.

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 incumbent licensor. Issuing one more license generates additional revenue (revenue effect), but reduces the incumbent's profits (rent dissipation effect)[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.

C.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 Δ_{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:[27] $z_{iTa}(\Delta_{Ta}, 0, \theta) = \pi_i(\Delta_{Ta}, 0, \theta) - \pi_i(0, \Delta_{Ta}, \theta)$. The only difference is that in the main model the innovator commits to sell on Firm 1 only, and hence Firm 1's symmetric 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 symmetric profit for Firm i is $\pi_i(0, \Delta_{Ta}, \theta)$. Using $z_{iTa}(\Delta_{Ta}, 0, \theta)$ and expression (4), 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 $P_1(\Delta^*_{Ta}, 0, \theta) = \left[\frac{1}{\theta} + \frac{2}{9}\right]$ and $P_2(0, \Delta^*_{Ta}, \theta) = \left[\frac{1}{\theta} - \frac{2}{9}\right]$; and expected demands $d_1(\Delta^*_{Ta}, 0, \theta) = \left[\frac{1}{2} + \frac{\theta}{9}\right]$ and $d_2(0, \Delta^*_{Ta}, \theta) = \left[\frac{1}{2} - \frac{\theta}{9}\right]$. Equilibrium auction bid, and payoff to the innovator, simplify to $z^*_{1Ta} = 4/9$, and $Z^*_{Ta} = 2/9$, respectively.*

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 Δ_{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*

[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.

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 $\theta \in \Theta$.*

C.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:

$$\max_{p_1} \pi_1(\Delta_T, p_1, p_2, \theta, r) = \max_{p_1} (p_1 - c + \Delta_T - r)\, d_1(p_1, p_2, \theta),$$

$$\max_{p_2} \pi_2(p_2, p_1, \theta) = \max_{p_2} (p_2 - c)\, d_2(p_1, p_2, \theta),$$

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 FOCs with respect to price, and solving the resulting system of two equations yields the following equilibrium profits:

$$\pi_1(\Delta_T, \theta, r) = \left[\frac{1}{\theta} + \frac{\Delta_T - r}{3}\right]\left[\frac{1}{2} + \frac{(\Delta_T - r)\theta}{6}\right],$$
$$\pi_2(\Delta_T, \theta, r) = \left[\frac{1}{\theta} - \frac{\Delta_T - r}{3}\right]\left[\frac{1}{2} - \frac{(\Delta_T - r)\theta}{6}\right].$$

At date 2, as can readily be shown, in equilibrium Firm 1 licenses innovation Δ_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:

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

The innovator chooses innovation Δ_T^* to maximize the following payoff:

$$Z_T = z_T\left(\Delta_T, \theta, r\right) + r \cdot d_1\left(p_1, p_2, \theta\right) - K_T\left(\Delta_T\right),$$

with the expected demand $d_1\left(p_1, p_2, \theta\right) = \frac{1}{2} + \frac{(\Delta_T - r)\theta}{6}$. Using expression (7), and taking the FOC with respect to Δ_T and r, yields the optimal innovation, royalty, and payoff for the innovator are:

$$\Delta_T^* = \frac{3}{8-\theta},$$

$$r_T^* = \frac{6}{\theta(8-\theta)},$$

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

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 Δ_T^* is increasing in downstream competition, θ.

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:

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

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

At date 2, as can readily be shown, in equilibrium Firm i licenses innovation Δ_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: $\pi_i\left(\Delta_i, \Delta_j, \theta\right) - z_{iM}\left(\Delta_i, \Delta_j, \theta\right) \geq \pi_i\left(0, \Delta_j, \theta\right)$, 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:

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

The innovator chooses innovation Δ_M^* to maximize the following payoff:

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

Using expression (7), and taking the FOC with respect to Δ_M and r respectively, we obtain the following equilibrium results:

$$\Delta_M^* = 1,$$

$$r_T^* = 1 + \frac{3}{2\theta},$$

$$Z_M^* = \frac{1}{2} + \frac{1}{4\theta}.$$

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, θ. 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:

$$\Delta Z = Z_T^* - Z_M^* = \frac{\theta + 1}{2\theta(8-\theta)} - (\frac{1}{2} + \frac{1}{4\theta}).$$

Let $\Delta Z = 0$, clearly there is a threshold point of θ, $\theta^* = 6.9$, 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 market-wide licensing, one can easily deduce that the equilibrium innovation has a U-shaped relationship with downstream competition. These key results under a fixed fee plus royal contract are equivalent to those in our main 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 θ^*, $\theta^* = 6.9$, 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 a U-shaped relationship between downstream competition and upstream innovation.

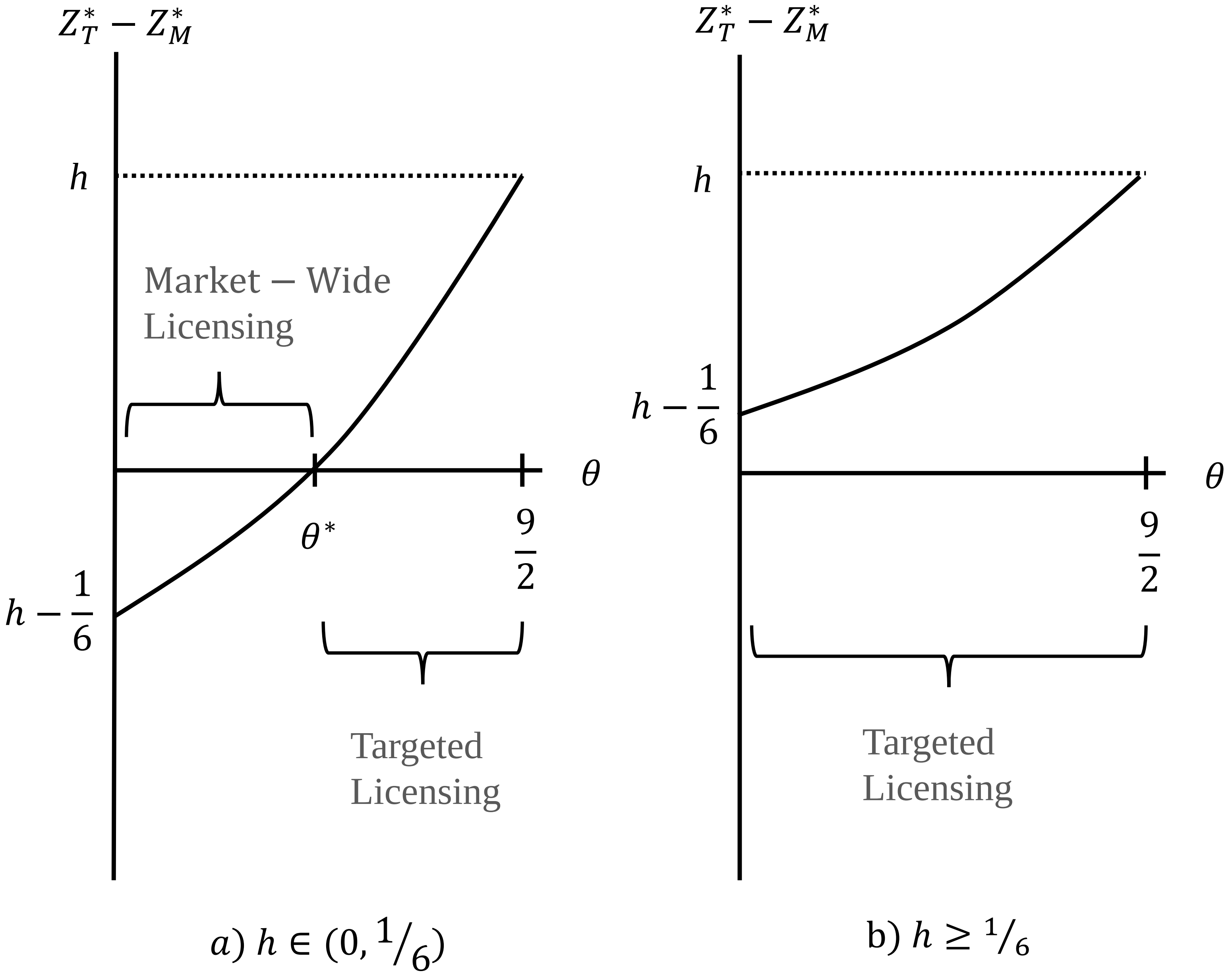
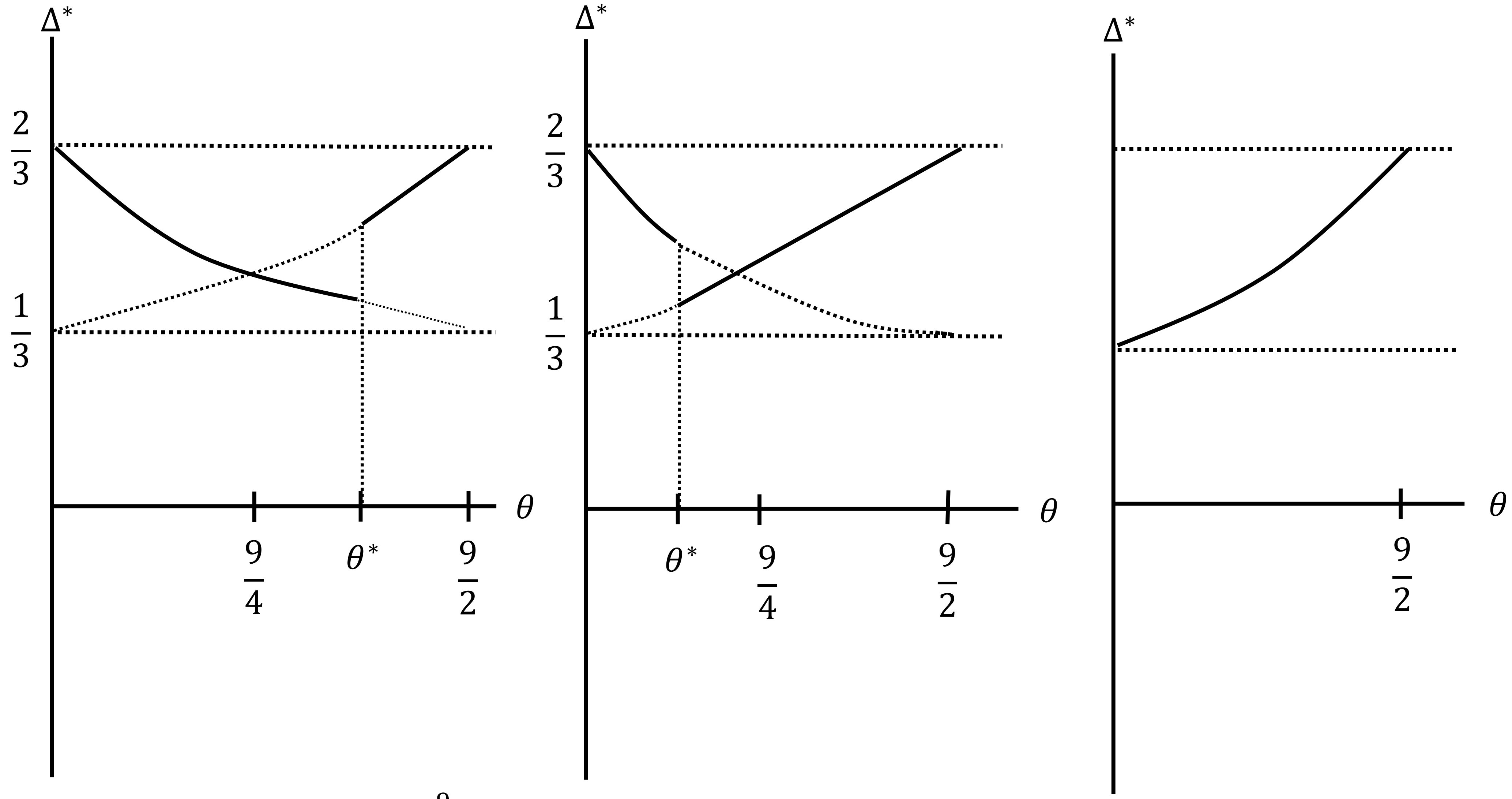


Figure 1: Product Market Competition and Licensing Strategy



a1) $h \in (0, {}^{1}/_{6})\,, \theta^{*}(h) \geq \frac{9}{4}$ a2) $h \in (0, {}^{1}/_{6})\,, \theta^{*}(h) < {}^{9}/_{4}$ b) $h \geq {}^{1}/_{6}$

Figure 2: Product Market Competition and Innovation