Appendix

A. Proofs and Extensions of the Theoretical Framework

A.1. Bertrand Competition

In this section, we present the proofs of the main model of Bertrand competition that are omitted from the main text.

A.1.1. Consumer Demand. We follow Vives (2000) and Häckner (2000) and consider an industry with n products that are produced at 0 marginal cost. We derive demand from the behavior of a representative consumer with a quadratic utility function

$$U(q)=\sum_{i=1}^{n}q^i\alpha^i-\frac{1}{2}\left(\sum_{i=1}^{n}(q^i)^2+2\gamma\sum_{i\neq j}q^iq^j\right),$$

where q^i is the quantity of product i, $\alpha^i>0$ measures product quality in a vertical sense, and γ represents the degree of substitutability between products. $1>\gamma>0$ ensures that the products are (imperfect) substitutes. The higher the γ, the more alike are the products. The resulting consumer maximization problem yields linear inverse demand for each product i given by $p^i=\alpha^i-q^i-\gamma\sum_{j\neq i}^{n}q^j$, where p^i is the price of product i. For simplicity, let us assume that the product quality of all the incumbents is identical, α^A for all the incumbents' existing products and α^E for the entrepreneur's potential product.

A.1.2. No Acquisition. Consider first the product market choices of an entrepreneur that is not acquired ($\neg acq$). If the project is successful (S), the resulting newly developed product competes against n other single-product incumbent firms. The entrepreneur's objective function is $\max_{p^E}p^Eq^E$, and the acquirer's (and all of he other incumbents') objective function is $\max_{p^A}p^Aq^A$. The n incumbents have product quality α^A, and the entrepreneur has product quality α^E. The entrepreneur's product market profit is given by

$$\pi^E_{\neg acq,S}=\frac{\gamma(n-1)+1}{(1-\gamma)(\gamma n+1)}\left(p^E_{\neg acq,S}\right)^2,$$

where

$$p^E_{\neg acq,S}=\frac{\alpha^E\{\gamma^2[(n+1)^2-5(n+1)+5]+3\gamma(n-1)+2\}-\gamma[\gamma(n-1)+1]\alpha^A n}{[\gamma(n-2)+2]\{\gamma[2(n+1)-3]+2\}}.$$

The acquirer's profit is equal to

$$\pi^A_{\neg acq,S}=\frac{\gamma(n-1)+1}{(1-\gamma)(\gamma n+1)}\left(p^A_{\neg acq,S}\right)^2,$$

where

$$p^A_{\neg acq,S}=\frac{\alpha^A\{\gamma^2[(n+1)^2-5(n+1)+5]+3\gamma(n-1)+2\}-\gamma[\gamma(n-1)+1][\alpha^A(n-1)+\alpha^E]}{[\gamma(n-2)+2]\{\gamma[2(n+1)-3]+2\}}.$$

In the special case of no vertical differentiation ($\alpha^A=\alpha^E$), these expressions simplify to

$$\pi^E_{\neg acq,S}=\frac{(\alpha^A)^2(1-\gamma)[1+(n-1)\gamma]}{[2+(n-2)\gamma]^2(1+n\gamma)}=\pi^A_{\neg acq,S}.$$

If the new project fails (F), the entrepreneur does not have any product to sell in $t=2$, and thus her profit is equal to $\pi^E_{\neg acq,F}=0$. The n incumbent firms including the acquirer each have a single existing product to sell, and thus their profit is equal to

$$\pi^A_{\neg acq,F}=\frac{(\alpha^A)^2(1-\gamma)[1+(n-2)\gamma]}{[2+(n-3)\gamma]^2[1+(n-1)\gamma]}.$$

A.1.3. Acquisition. Next consider the product market choices of an acquirer in the case of an acquisition (acq). If the project is successful, he becomes a two-product oligopolist who optimally chooses quantities for his new and his old product and competes against $n-1$ other single-product incumbents. The acquirer's objective function is

$$\max_{p^A_{old},p^A_{new}} p^A_{old}q^A_{old}+p^A_{new}q^A_{new},$$

whereas the remaining $n-1$ other single-product firms maximize single-product profits.

The profit of the multi-product incumbent acquirer is

$$\pi^A_{acq,S} = p^A_{old} q^A_{old} + p^A_{new} q^A_{new},$$

where

$$p^A_{old} = \frac{1}{2}\left[\frac{\alpha^A - \alpha^E}{2} + \frac{[2+\gamma(2n-1)][2+\gamma(n-2)]}{[2+\gamma(2n-2)][2+\gamma(n-1)]-2\gamma^2}\tilde{p}\right]$$
$$p^A_{new} = \frac{1}{2}\left[\frac{\alpha^E - \alpha^A}{2} + \frac{[2+\gamma(2n-1)][2+\gamma(n-2)]}{[2+\gamma(2n-2)][2+\gamma(n-1)]-2\gamma^2}\tilde{p}\right]$$

and

$$q^A_{old} = \frac{1}{2}\left[\frac{1}{1-\gamma}\frac{\alpha^A - \alpha^E}{2} + \frac{[2+\gamma(2n-1)][2+\gamma(n-2)]}{[2+\gamma(2n-2)][2+\gamma(n-1)]-2\gamma^2}\frac{1+\gamma(n-2)}{1+\gamma(n-1)}\tilde{q}\right]$$
$$q^A_{new} = \frac{1}{2}\left[\frac{1}{1-\gamma}\frac{\alpha^E - \alpha^A}{2} + \frac{[2+\gamma(2n-1)][2+\gamma(n-2)]}{[2+\gamma(2n-2)][2+\gamma(n-1)]-2\gamma^2}\frac{1+\gamma(n-2)}{1+\gamma(n-1)}\tilde{q}\right],$$

where $\tilde{p} = p^A_{\neg acq,S} + p^E_{\neg acq,S}$ and $\tilde{q} = \frac{\gamma(n-1)+1}{(1-\gamma)(\gamma n+1)}\tilde{p}$ denote the sum of prices and the sum of quantities of the acquirer's two products if these two products were produced by two separate single-product competitors.

In the special case of no vertical differentiation ($\alpha^A = \alpha^E$), the profit of the multiproduct acquirer simplifies to

$$\pi^A_{acq,S} = \frac{(\alpha^A)^2(1-\gamma)[1+(n-2)\gamma][2+\gamma(2n-1)]^2}{2(1+n\gamma)\{2+(3n-4)\gamma+[1+(n-3)n]\gamma^2\}^2}.$$

If the project is unsuccessful, the acquirer can still sell the old existing product in $t=2$ and only has to compete against $n-1$ other single-product incumbents. In this case the resulting profit for the acquirer is

$$\pi^A_{acq,F} = \frac{(\alpha^A)^2(1-\gamma)[1+(n-2)\gamma]}{[2+(n-3)\gamma]^2[1+(n-1)\gamma]}.$$

Comparing these expressions yields the profit ranking for the acquirer

$$\pi^A_{acq,S} > \pi^A_{acq,F} = \pi^A_{\neg acq,F} > \pi^A_{\neg acq,S} > 0$$

and for the entrepreneur

$$\pi^E_{\neg acq,S} > \pi^E_{\neg acq,F} = 0.$$

In addition, with these expressions, we obtain the central inequality characterizing development gains of the new product for the entrepreneur and the acquirer, which is given by

$$\Delta^E \equiv \pi^E_{\neg acq,S} - \pi^E_{\neg acq,F} > \pi^A_{acq,S} - \pi^A_{acq,F} \equiv \Delta^A,$$

which holds for $1 > \gamma > 0$.

A.1.4. Product Market Overlap.

Proof of Proposition 1. From inequality (3), it immediately follows that an incumbent firm acquires a project and continues development if $k \leq k^A$ and that an independent entrepreneur continues if $k \leq k^E$. Equation (4) shows that the thresholds $k^E > k^A$ if and only if $\rho^E \Delta^E > \rho^A \Delta^A$. Rearranging the inequality yields the proposition.

Using the expressions above for any positive product market overlap $1 > \gamma > 0$, we have $\Delta^E > \Delta^A$. For $\gamma = 0$ and $\gamma = 1$, we have $\Delta^E = \Delta^A$. Therefore, for any product market overlap, even if the incumbent has a development advantage (i.e., $\rho^A > \rho^E$), he still may have a lower willingness to develop the project than the entrepreneur. □

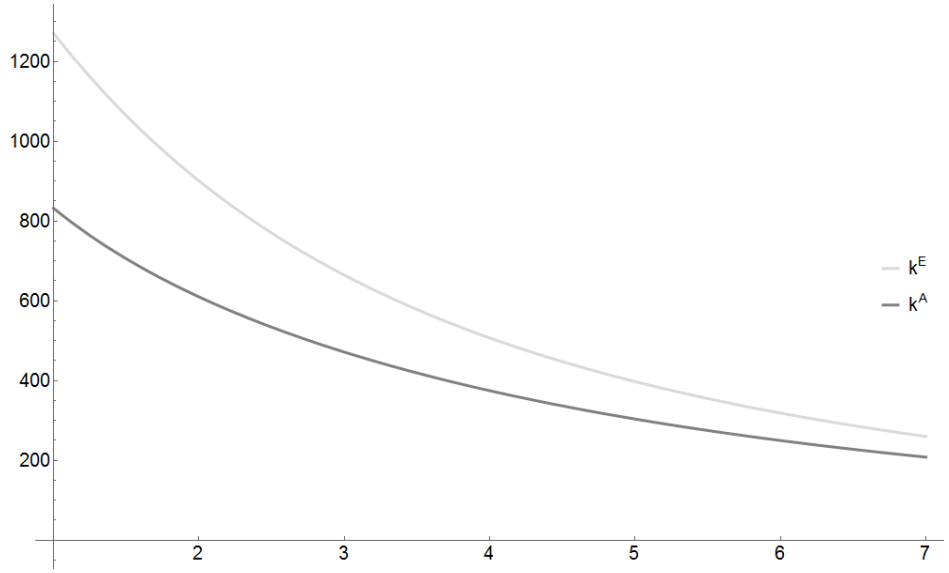
A.1.5. Competition.

Proof of Proposition 2. Note that the difference between the thresholds is given by $k^E - k^A = \rho^E \Delta^E - \rho^A \Delta^A$. Proposition 1 establishes that $\Delta^E - \Delta^A > 0$ for any $1 > \gamma > 0$. Substituting the profit expressions $\pi^E_{\neg acq,S}$, $\pi^E_{\neg acq,F}$, $\pi^A_{acq,S}$, and $\pi^A_{acq,F}$ and differentiation of $\Delta^E - \Delta^A$ with respect to n establishes the result. □

Figure A1 illustrates this point by plotting the development thresholds k^E and k^A as a function of the number of incumbents for the case where $\rho^E = \rho^A$. These thresholds are closer together when there are more existing incumbents because the difference $\Delta^E - \Delta^A$ shrinks as n increases. In the limit in which the number of existing products n goes to infinity, the acquiring incumbent has a vanishingly small share of the existing market and thus all of the

cannibalization losses fall on the other competitors. As a result, for $n \to \infty$, Δ^E and Δ^A are the same and hence the continuation policies of the entrepreneur and the acquirer are identical.

Figure A1. Development Cost Thresholds and Competition



This graph plots the optimal development cost thresholds of the entrepreneur (k^E, light gray) and the acquirer (k^A, dark gray) as a function of the number of incumbents n. The other parameter values are $\alpha^A = \alpha^E = 100$, $\gamma = 0.375$, $\rho^A = \rho^E = 0.75$, and $L = 20$.

A.1.6. Patent Life and Future Competition.

Proof of Proposition 3. After T^A years, the patent on the incumbent's existing product expires and generic undifferentiated entry for this product occurs. Due to undifferentiated Bertrand competition, profits of the acquirer's existing product drop to zero after T^A. Until that time T^A, the acquirer's development gain from developing the new product is equal to $T^A \Delta^A$. Similarly, the entrepreneur's development gain over that time span is $T^A \Delta^E$.

In addition, after T^A and until T^E, the newly developed product still earns positive profits because it is differentiated from the generic entry that drives the profits of the existing drug to zero. Denote the per-period development gains of the new product for the entrepreneur and the acquirer in the presence of generic competition for the acquirer's existing product by Δ^E_{gen} and Δ^A_{gen}.

First, these development gains are smaller than the previous expressions, $\Delta^E_{gen} < \Delta^E$ and $\Delta^A_{gen} < \Delta^A$. When a generic product that is undifferentiated from the acquirer's existing product enters, it not only drives profits of that existing product to zero, but it also reduces the profits

of the newly developed product. This occurs because the generic product is a perfect substitute for the acquirer's existing product and an imperfect substitute for the newly developed product.

Second, the development gains of the new product under generic competition for the existing product are equal to each other; $\Delta_{gen} = \Delta^E_{gen} = \Delta^A_{gen}$. This is because generic competition for the acquirer's existing drug has already reduced all of the profits of the acquirer's existing drug, and thus development of the new product does not replace any of the existing product's profits for the acquirer.

After T^E, generic entry also occurs for the newly developed product occurs, thereby reducing all profits to zero.

The development decisions of the entrepreneur d^E_{gen} and the acquiring incumbent d^A_{gen} are now determined by

$$\rho^E\left(\frac{1-\delta^{T^A}}{1-\delta}\Delta^E + \frac{\delta^{T^A}-\delta^{T^E}}{1-\delta}\Delta_{gen}\right) - k \geq L \tag{9}$$

$$\rho^A\left(\frac{1-\delta^{T^A}}{1-\delta}\Delta^A + \frac{\delta^{T^A}-\delta^{T^E}}{1-\delta}\Delta_{gen}\right) - k \geq L, \tag{10}$$

where Δ_{gen} is the development gain for the entrepreneur and the incumbent in the presence of undifferentiated generic competition after the expiration of the acquirer's existing product's patent in T^A years.

Therefore, the resulting difference in the development thresholds is given by $\rho\frac{1-\delta^{T^A}}{1-\delta}(\Delta^E - \Delta^A)$. This difference is increasing in T^A if $\frac{\rho^A}{\rho^E} \leq \frac{\Delta^E - \Delta_{gen}}{\Delta^A - \Delta_{gen}}$, which establishes the proposition. □

A.1.7. Acquisition Decision.

Proof of Proposition 4. The acquirer decides to acquire at a takeover price P if

$$d^A[\rho^A\pi^A_{acq,S} + (1-\rho^A)\pi^A_{acq,F} - k] + (1-d^A)(L + \pi^A_{acq,F}) - P \geq d^E[\rho^E\pi^A_{\neg acq,S} + (1-\rho^E)\pi^A_{\neg acq,F}] + (1-d^E)\pi^A_{\neg acq,F}, \tag{11}$$

where $d^i \in \{0,1\}$ for $i = \{E,A\}$ is the development decision for the owner of the project in $t=1$.

To compensate the entrepreneur for selling the project, the acquirer must pay a price P that

is equal to the expected payoff of the project when the entrepreneur remains independent. Thus,

$$P = d^E(\rho^E \Delta^E - k) + (1 - d^E)L. \tag{12}$$

Substituting the takeover price (12) into the inequality for the acquisition decision (11) and solving for each of the cases of k establishes the acquisition choices outlined in the main text for the case where $1 > \gamma > 0$.

Consider the case in which there is no product market overlap ($\gamma = 0$) and no development synergy advantage ($\rho^A = \rho^E$). As a result, the incremental profit from developing the product is the same for the incumbent acquirer and the entrepreneur, their continuation thresholds coincide ($k^A = k^E$), and the incumbent acquirer's profit is unaffected by the entrepreneur's development success. Therefore, the two players value the project exactly the same, and the incumbent acquirer is always indifferent between acquiring or not acquiring the project. If $\gamma = 0$ and $\rho^A < \rho^E$, the acquirer strictly prefers not to acquire the entrepreneur. This establishes the proposition. □

A.1.8. Welfare. We now show under what conditions killer acquisitions are welfare-decreasing. This is the case whenever $k^E \geq k > k^A$ and the social surplus resulting from no acquisition (and continued development) is higher than when there is no acquisition (and termination). Under a social welfare standard that uses the unweighted sum of consumer surplus and producer surplus, this is given by the following inequality

$$\rho^E \pi^E_{\neg acq,S} - k + n[\rho^E \pi^A_{\neg acq,S} + (1 - \rho^E)\pi^A_{\neg acq,F}] + \rho^E CS_{\neg acq,S} + (1 - \rho^E)CS_{\neg acq,F} \geq P + (\pi^A_{acq,F} + L - P) + CS_{acq,F},$$

where P is the transaction price that is just a transfer between incumbent and entrepreneur and $CS_{\neg acq,S}$ and $CS_{\neg acq,F} = CS_{acq,F}$ are the consumer surplus values under the different scenarios. Recall that $\pi^A_{\neg acq,F} = \pi^A_{acq,F}$; then rewriting this condition yields

$$(\rho^E \pi^E_{\neg acq,S} - k - L) + \rho^E (CS_{\neg acq,S} - CS_{\neg acq,F}) \geq n\rho^E (\pi^A_{\neg acq,F} - \pi^A_{\neg acq,S}).$$

The first term in parentheses on the left-hand side is the entrepreneur's net expected profit gain from continuing development. This is positive in the killer acquisitions region $k^E \geq k > k^A$. The second term is the expected increase in consumer surplus due to continued development, which is also positive both because there is more product variety and prices are lower. The term on the right-hand side of the inequality is the expected loss in profit for the n incumbents, and it is also positive. We can derive a sufficient condition for killer acquisitions to be welfare-reducing by setting the first term to zero (i.e., $k = k^E$ so the entrepreneur is indifferent between developing and not developing). This yields the following condition:

$$CS_{\neg acq,S} - CS_{\neg acq,F} \geq n(\pi^A_{\neg acq,F} - \pi^A_{\neg acq,S}). \tag{13}$$

Hsu and Wang (2005) derive expressions for consumer surplus and total welfare under differentiated goods oligopoly. Using their expressions, we obtain the following expression for the increase in consumer surplus:

$$CS_{\neg acq,S} - CS_{\neg acq,F} = \frac{(n+1)(1+\gamma n)}{2} q^2_{n+1} - \frac{n[1+\gamma(n-1)]}{2} q^2_n,$$

where q_n and q_{n+1} denote the equilibrium quantities when there are n and $n+1$ firms in the market.

It is now straightforward to show that the sufficient condition for killer acquisitions to be welfare-reducing given by inequality (13) is always satisfied for any degree of product substitution under differentiated Bertrand competition with a single incumbent ($n = 1$). For $n \geq 2$, even without vertical differentiation, the inequality is satisfied under differentiated Bertrand competition as long as the entrant's product is sufficiently differentiated (i.e., $\gamma < \gamma^W$) from the existing incumbents.

Furthermore, as n increases the threshold γ^W below which killer acquisitions decrease, welfare also decreases, thus increasing the region under which killer acquisitions do not necessarily reduce welfare. However, from Proposition 2, we know that as n increases, the region in which killer acquisitions occur shrinks. Thus, it is precisely in the cases in which killer acquisitions do not occur for a large set of parameter values that their social welfare impact is also potentially beneficial.

A.2. Cournot Competition

Consider the same setting as in our main model, but assume that firms compete in quantities rather than prices in the competition stage in $t=2$.

If the entrepreneur remains independent in $t=0$, the payoffs in $t=2$ are

$$\begin{aligned}
\pi^E_{\neg acq,F} &= 0 \\
\pi^A_{\neg acq,F} &= \frac{(\alpha^A)^2}{[2+\gamma(n-1)]^2} \\
\pi^E_{\neg acq,S} &= \frac{\{\alpha^E[2+\gamma(n-1)]-\alpha^A\gamma n\}^2}{[(2-\gamma)(\gamma n+2)]^2} \\
\pi^A_{\neg acq,S} &= \frac{[2\alpha^A-\alpha^E\gamma]^2}{[(2-\gamma)(\gamma n+2)]^2}.
\end{aligned}$$

If the incumbent acquires the entrepreneur in $t=0$, the payoffs in $t=2$ are

$$\pi^A_{acq,F} = \frac{(\alpha^A)^2}{[2+\gamma(n-1)]^2}$$

and

$$\pi^A_{acq,S} = p^A_{old}q^A_{old}+p^A_{new}q^A_{new},$$

where $p^A_{old}=q^A_{old}+\gamma q^A_{new}$ and $p^A_{new}=q^A_{new}+\gamma q^A_{old}$ and

$$\begin{aligned}
q^A_{old} &= \frac{1}{2}\left[\frac{\alpha^A-\alpha^E}{2(1-\gamma)}+\frac{2+\gamma(n-2)}{2+\gamma(n-\gamma)}\left(\frac{\alpha^A+\alpha^E}{2}-\gamma\frac{(n-1)\alpha^A}{2+\gamma(n-2)}\right)\right] \\
q^A_{new} &= \frac{1}{2}\left[\frac{\alpha^E-\alpha^A}{2(1-\gamma)}+\frac{2+\gamma(n-2)}{2+\gamma(n-\gamma)}\left(\frac{\alpha^A+\alpha^E}{2}-\gamma\frac{(n-1)\alpha^A}{2+\gamma(n-2)}\right)\right].
\end{aligned}$$

In the special case of no vertical differentiation ($\alpha^A=\alpha^E$), the profit for the multiproduct acquirer simplifies to

$$\pi^A_{acq,S} = \frac{(\alpha^A)^2(2-\gamma)^2(1+\gamma)^2}{2(2+\gamma n-\gamma^2)^2}.$$

Defining Δ^E and Δ^A with these payoffs and using the same logic of the proofs above establishes all the propositions as in our main model.

A.3. The Market for Ownership

A.3.1. Multiple Potential Acquirers. In the baseline version of our model we assume that one of the n incumbents is chosen at random to be the potential acquirer of the entrepreneur's project. Assume the development cost k is in the region in which killer acquisitions can occur in the case of a single bidder, $k^E > k > k^A$, and that $\rho^E(\pi^A_{acq,F} - \pi^A_{\neg acq,S}) \geq \rho^E\Delta^E - k - L$ such that an acquirer acquires the entrepreneur (and does not develop the project). The acquirer has to pay the acquisition price $P = \rho^E\Delta^E - k$ (i.e., at least the entrant's expected profits under competition), but the benefits from eliminating a new competitor are diffuse and also accrue to the other incumbent. In particular, the acquirer earns $\pi^A_{acq,F} + L - P$, while all the other $n-1$ incumbents earn $\pi^A_{acq,F} > \pi^A_{acq,F} + L - P$ because for $k^E > k > k^A$, we have $\rho^E\Delta^E - k > L$. This leads to a potential free-riding problem known as the "volunteer's dilemma" (Diekmann, 1985) or, more broadly, to the problem of costly private provision of a public good (Bliss and Nalebuff, 1984).

Let us now assume that $n_b \leq n$ incumbents can acquire the entrepreneur.[48] It is never optimal for any of the n_b bidders to bid any price other than $P = \rho^E\Delta^E - k$ because paying a higher price reduces the bidder's profits and bidding less means that the entrepreneur would reject the bid. First, there are therefore multiple pure-strategy equilibria in which one of the n_b incumbents bids $P = \rho^E\Delta^E - k$, all the other incumbents do not bid, and the bidding incumbent acquires the entrepreneur. All these pure-strategy equilibria are essentially identical to the single bidder case analyzed in our baseline model. Second, for $n_b \geq 2$ there exists a mixed-strategy equilibrium in which each of the n_b bidders chooses to bid $P = \rho^E\Delta^E - k$ with probability p and to not make any bid with probability $1-p$. In case of a tie in which several bidders make the same highest bid, one of them is chosen randomly.

If the bidder chooses not to make a bid, he obtains

$$(1-p)^{n_b-1}[\rho^E\pi^A_{\neg acq,S} + (1-\rho^E)\pi^A_{\neg acq,F}] + [1-(1-p)^{n_b-1}]\pi^A_{acq,F},$$

which is the sum of the expected payoffs when no bidder bids and when at least one bidder makes a bid.

[48] Outside bidders are irrelevant in our model because they always have exactly the same valuation for the entrepreneur's project as the entrepreneur herself.

If the bidder chooses to bid $P=\rho^E\Delta^E-k$, he obtains

$$\sum_{j=0}^{n_b-1}\binom{n_b-1}{j}p^j(1-p)^{n_b-1-j}\left[\frac{1}{j+1}(\pi^A_{acq,F}+L-P)+\frac{j}{j+1}\pi^A_{acq,F}\right],$$

which can be rewritten in the following way

$$\pi^A_{acq,F}-\sum_{j=0}^{n_b-1}\binom{n_b-1}{j}p^j(1-p)^{n_b-1-j}\frac{1}{j+1}(\rho^E\Delta^E-k-L),$$

where the expected payment that the bidder makes depends on the number of other bidders who also bid.

In equilibrium, each bidder is indifferent between bidding P and not bidding, and thus we have

$$\pi^A_{acq,F}-\sum_{j=0}^{n_b-1}\binom{n_b-1}{j}p^j(1-p)^{n_b-1-j}\frac{1}{j+1}(\rho^E\Delta^E-k-L)=$$
$$(1-p)^{n_b-1}[\rho^E\pi^A_{\neg acq,S}+(1-\rho^E)\pi^A_{\neg acq,F}]+[1-(1-p)^{n_b-1}]\pi^A_{acq,F},$$

which we can rearrange to obtain

$$p=1-\left[\frac{\rho^E\Delta^E-k-L}{\rho^E(\pi^A_{acq,F}-\pi^A_{\neg acq,S})}\sum_{j=0}^{n_b-1}\binom{n_b-1}{j}p^j(1-p)^{n_b-1-j}\frac{1}{j+1}\right]^{\frac{1}{n_b-1}}.$$

This equation defines the individual equilibrium mixing probability p. It has a very intuitive interpretation. As in the single acquirer case, the main driving force is the ratio of the replacement effect ($\rho^E\Delta^E-k-L$) to the efficiency effect ($\rho^E(\pi^A_{\neg acq,F}-\pi^A_{\neg acq,S})$). The larger the efficiency effect relative to the replacement effect is, the more likely an acquirer is to make an acquisition bid for the entrepreneur. This is essentially the same as the inequality in (5), which requires that the ratio of $\rho^E\Delta^E-k-L$ (replacement effect) to $\rho^E(\pi^A_{\neg acq,F}-\pi^A_{\neg acq,S})$ (efficiency effect) is smaller than one.

In addition, the number of potential acquirers n_b also plays a crucial role now. There are two forces at work here that work in opposite directions. First, as the number of potential bidders increases, the incentive to free ride on another bidder's bid (and killer acquisition) increases.

This can be seen by looking at the exponent $\frac{1}{n_b-1}$ on the right-hand side of the equation that reduces the right-hand side because the term inside the brackets is positive and strictly smaller than one. This is the familiar free-riding effect in the volunteer's dilemma. Second, as the number of potential acquirers increases, the expected payment that an acquirer has to make when he decides to make a bid decreases. This occurs because he is less likely to be chosen as the "winning bidder" who has to pay the acquisition price to the entrepreneur.[49] The term inside the summation on the right-hand side captures this effect; it decreases with n_b and thus raises the probability that a potential acquirer will make a bid for the entrepreneur.

We can further rewrite the equation defining p to obtain

$$p = 1 - \left[\frac{\rho^E \Delta^E - k - L}{\rho^E (\pi^A_{acq,F} - \pi^A_{\neg acq,S})} \frac{1-(1-p)^{n_b}}{n_b p} \right]^{\frac{1}{n_b-1}}.$$

Therefore the probability that there will be a killer acquisition (i.e., that at least one bidder will acquire the entrepreneur) is defined by

$$1-(1-p)^{n_b} = 1 - \left[\frac{\rho^E \Delta^E - k - L}{\rho^E (\pi^A_{acq,F} - \pi^A_{\neg acq,S})} \frac{1-(1-p)^{n}_b}{n_b p} \right]^{1+\frac{1}{n_b-1}}.$$

Using implicit differentiation, we can show that this probability strictly increases as the number of potential bidders n_b increases. In other words, the increase in the number of potential acquirers n_b together with the above-mentioned second effect (i.e., the effect arising from an acquirer having to make a lower expected payment) dominate the first effect (i.e., the conventional free-riding effect in the volunteer's dilemma).

Finally, note that these comparative statics of the mixed-strategy equilibrium are for the case where we hold the number of incumbents n fixed and focus on the region in which killer acquisitions occur. Changing the number of incumbents n, however, also affects the ratio of the replacement effect to the efficiency effect and, more importantly, shrinks the region $k^E \geq k > k^A$ in which killer acquisitions are possible. Therefore, comparative statics of the mixed-strategy equilibrium with respect to the number of incumbents who are all allowed to

[49] This effect would be absent in an (albeit unrealistic) all-pay auction setup in which each bidder always has to pay his bid.

bid lead to ambiguous predictions.

A.3.2. Asymmetries between Potential Acquirers. Consider now the case in which there are multiple potential acquirers denoted by A_i whose products can differ in their degree of differentiation from the entrepreneur's project (i.e., different degree of substitutability γ^{A_iE}) and can have different synergy advantages (i.e., different development probability ρ^{A_i}). For simplicity, we assume that there is no vertical differentiation. The linear inverse demand for the existing product of potential acquirer A_i is now given by $p^{A_i}=\alpha-q^{A_i}-\gamma\sum_{A_j\neq A_i}^{n}q^{A_j}-\gamma^{A_iE}q^{E}$. We assume that the development synergies are not too large such that k^{A_i}, which denotes the development threshold of the potential acquirer A_i defined by $k^{A_i}=\rho^{A_i}\Delta^{A_i}-L$, is smaller than k^E for each potential acquirer A_i. Formally, this is the case if $\frac{\Delta^E}{\Delta^{A_i}}>\frac{\rho^{A_i}}{\rho^E}$.

First, as discussed before, the parties are indifferent as to who owns the projects if development costs are such that $k>k^E$ because everybody chooses not to develop the project in that case and has the same valuation.

Second, if development costs are in the killer acquisitions region (i.e., $k^E>k>k^{A_i}$) for all A_i potential acquirers, the potential acquirer who is the least differentiated from the entrepreneur will have the highest valuation for the entrepreneur's project among all potential acquirers. Recall that in this region an acquirer is willing to acquire the entrepreneur if

$$L+\pi_{acq,F}^{A_i}-(\rho^E\Delta^E-k)\geq\rho^E\pi_{\neg acq,S}^{A_i}+(1-\rho^E)\pi_{\neg acq,F}^{A_i},$$

which we can rewrite to obtain the familiar condition

$$\underbrace{\rho^E(\pi_{acq,F}^{A_i}-\pi_{\neg acq,S}^{A_i})}_{\text{efficiency effect}}-\underbrace{(\rho^E\Delta^E-k-L)}_{\text{replacement effect}}\geq 0.$$

The replacement effect is the same for all the acquirers because they all shut down the project upon acquisition. The efficiency effect, however, is largest for the potential acquirer A_i with the product that is the least differentiated from the entrepreneur's project (i.e., the highest γ^{A_iE}). To see this, note that in case of a killer acquisition, all incumbents earn the same profit $\pi_{acq,F}^{A_i}=\pi_{acq,F}$. If the killer acquisition does not occur and the entrepreneur successfully

develops the project, $\pi^{A_i}_{\neg acq,S}$ will be the lowest profit for the incumbent with the least degree of differentiation from the entrepreneur. Thus, the incumbent with the most closely related product to the entrepreneur's project will have the highest valuation to acquire it. Importantly, this result holds even if potential acquirers differ in their development capabilities ρ^{A_i} because none of the potential acquirers would want to continue the project.

Third, this unambiguous result that the least differentiated potential acquirer has the highest valuation among all potential acquirers continues to hold if the potential acquirers have the same development capabilities (i.e., $\rho^{A_i} = \rho^A$ for all A_i) but differ in their degree of differentiation such that at least some (or all) of the potential acquirers have development thresholds $k^{A_i} > k$ (and thus they would continue development following an acquisition), while the remaining potential acquirers have thresholds $k^{A_i} < k$ (and thus they would kill the project following an acquisition). Because the potential acquirers only differ in their degree of differentiation from the entrepreneur's project, the potential acquirer with the highest overlap $\gamma^{A_i E}$ (i.e., the most closely related product) has the lowest k^{A_i}. Denote this potential acquirer by A_h. As we showed above, all other potential killer acquirers with $k^{A_i} > k$ have a strictly lower net gain from acquisition than this acquirer with his overlap $\gamma^{A_h E}$. For this acquirer, the net gain from acquisition is equal to

$$G^{A_h} = \rho^E(\pi^{A_h}_{acq,F} - \pi^{A_h}_{\neg acq,S}) - (\rho^E \Delta^E - k - L) \geq \rho^E(\pi^{A_h}_{acq,F} - \pi^{A_h}_{\neg acq,S}) - (\rho^E \Delta^E - \rho^A \Delta^{A_h}),$$

where we used the fact that for $k + L = \rho^A \Delta^{A_i}$, this potential acquirer is just indifferent between developing and not developing the project. The expression after the inequality is the same as the net gain from acquisition for all potential acquirers with $k^{A_i} < k$:

$$G^{A_i} = \rho^E(\pi^{A_i}_{acq,F} - \pi^{A_i}_{\neg acq,S}) - (\rho^E \Delta^E - \rho^A \Delta^{A_i}).$$

This net gain is again a trade-off between the efficiency effect (first term) and the replacement effect (second term). It remains to show that the net gain for potential acquirer A_h is larger than for any other acquirer A_i. Both the efficiency effect as well as the replacement effect are largest for the acquirer A_h, and thus it is not a priori clear whether this acquirer will have the highest valuation for the entrepreneur's project. However, under both Bertrand and Cournot competition, G^{A_h} is strictly larger than any other G^{A_i}. This is because the impact of increasing product over-

lap is greater on the efficiency effect than on the replacement effect. Thus, the potential acquirer with the largest product overlap generally has the strongest incentive to acquire the entrepreneur if potential acquirers only differ in the degree of product differentiation from the entrepreneur.

Fourth, this acquisition value result no longer holds if potential acquirers also differ with respect to their development capabilities ρ^{A_i}. If development capabilities ρ^{A_i} and degrees of product differentiation from the entrepreneur's project γ^{A_iE} are such that at least some (or all) of the potential acquirers have development thresholds $k^{A_i} > k$, it is possible that a continuing acquirer with less overlap (lower γ^{A_iE}) but higher development capability (higher ρ^{A_i}) will have the highest valuation for the entrepreneur's project. This can be seen by writing out the net gain from acquisition for a continuing acquirer A_i with project development probability ρ^{A_i}:

$$G^{A_i} = \rho^E(\pi^{A_i}_{acq,F} - \pi^{A_i}_{\neg acq,S}) - (\rho^E\Delta^E - \rho^{A_i}\Delta^{A_i}).$$

For ρ^{A_i} sufficiently high (but still low enough such that $\frac{\Delta^E}{\Delta^{A_i}} > \frac{\rho^{A_i}}{\rho^E}$ is satisfied), this net gain is larger than that of the potential (killer or continuing) acquirer with the highest overlap. Conversely, as we showed above it also possible that a killer acquirer with more overlap (higher γ^{A_iE}) but a slightly lower development capability (lower ρ^{A_i}) will have the highest valuation for the entrepreneur's project. As in the case with a single potential acquirer, the relative magnitudes of the replacement effect and the efficiency effect play a crucial role because they determine the identity of the potential acquirer with the highest valuation.

B. Cleaning Pharmaprojects Data

To build our analytical dataset at the drug project level, we use Pharmaprojects from Pharma Intelligence. Pharmaprojects is a comprehensive dataset that tracks drug projects from a very early stage through to launch or discontinuation. Pharmaprojects provides nearly universal coverage of all candidate drugs developed or under development for eventual sale in the US market, along with the originating firm associated with each drug project. In this Appendix, we describe the process involved in cleaning the data.

B.1. Identifying Originators of Drug Projects

Our first challenge in using Pharmaprojects data for our analyses was to identify the developer of each drug project at each point in time, particularly pre- and post-acquisition. In the raw dataset, Pharmaprojects typically updates the "originator" firm name associated with each project. More specifically, if the project was acquired, the acquiring firm is typically erroneously listed as the originator of the project in the raw Pharmaprojects data. We therefore reconstruct the original originator firm in such cases.

To do so, we make use of two additional fields in the dataset. The first is the "overview" field, which intends to provide a background of the drug project and thus often includes the name of the original firm associated with the project in the case of acquisitions. For example, the drug Trastuzumab had the originator as "Roche" when it was initially developed by Genentech. The overview text reads "Trastuzumab is a humanized MAb to HER2, a cell surface oncoprotein which is overproduced in breast and ovarian cancers, under development by Genentech (Roche)," and hence we could use this information to extract the original originator as Genentech.

The second is the "latest change" field, which also would often contain details of acquisition events, including the associated firm names. For example, the field often read "Firm XYZ acquired by Firm ABC," which we would use to impute the original originator name as "Firm XYZ."

To extract the original originator firm from these fields, we used regular expressions and phrases such as "X acquired by Y" or "developed by X." We algorithmically created a list of original originators and the acquiring firms, and we checked them against our M&A datasets from SDC and Recap IQ.

B.2. Merging Pharmaprojects with Acquisition Data

Once we had a dependable measure of the true originator firms, our second challenge in using Pharmaprojects was to standardize originator firm names for matching with other datasets, including M&A events. We did so first by using the Stata program "stnd_compname" (Wasi and Flaaen, 2015), which isolated the stem name for each originator firm associated with each project in Pharmaprojects. We then checked all non-exact matching manually to confirm accuracy.

B.3. Categorizing Development Milestones

Pharmaprojects comprehensively documents the occurrence and timing of key product development milestones (e.g., "new patent application," "target identified," "first launch," and "additional registration for clinical trial"), including drug discontinuations. We aggregate the 28 events tracked by Pharmaprojects into three categories: development activities and events, termination events, and neutral events that impart little information regarding the progress (or termination) of drug development. Development events reflect both scientific milestones and important steps in the commercialization process for the underlying drug project. Pharmaprojects therefore allows us to identify and capture milestones that signify development of a drug, including, but not limited to, progress through clinical trials. The table "Measuring Drug Development" details all events and activities that comprise our main dependent variable.

Examining the patterns in development events and activities over the life cycle of active drug projects, we see that commercialization-related activity increases as a share of development activity over time (see table "Share of Development Events, by Project Age"). Therefore capturing such activities over and above clinical trial progress is especially important for inferring post-acquisition development activity.

In addition to our main results using development milestones, we also run supplementary analysis using progression through phases of clinical trials as the dependent variable, which involves supplementing the Pharmaprojects data with Pharma Intelligence's Trialtrove data on clinical trials, linked at the project level. The data construction and results of this analysis are described in detail Appendix E.

Table B1
Measuring Drug Development

This table presents a list of events recorded in Pharmaprojects to track the development process of each drug. The events are listed in alphabetical order. Each of these events is coded into one of the three categories: development events, discontinuation events, and neutral events with little information regarding drug development progress (denoted as "–" in the table).

Events	**Development Event?**
Additional launches	Yes
Additional registrations	Yes
Change in disease status	–
Change in global status	–
Change in licensee status	–
Compounds identified	Yes
Development continuing	Yes
Discontinued products	No
First launches	Yes
First registrations	Yes
Global status reversion	–
Licenses discontinued	–
Licensing opportunities	–
Mechanism identified	Yes
Names granted	Yes
New chemical structure	Yes
New disease	Yes
New licensees	Yes
New patent applications	Yes
New product	–
New therapeutic activity	Yes
No development reported	–
Novel target reported	Yes
Orphan drug status granted	Yes
Registration submissions	–
Suspended products	No
Target identified	Yes
Withdrawn products	No

Table B2
Share of Development Events, by Project Age

This table presents a list of the share of development event/activities that comprise the dependent variable in our main analyses, across different ages of drug projects. The top panel presents the fully disaggregated tabulation. To highlight changes in the type of events over time, the bottom panel collapses event/activities into commercialization-related activity (first launches, additional launches, first registrations, additional registrations, names granted, new licensees, new patent applications, orphan drug status granted) and science-related activity (compounds identified, mechanisms identified, new chemical structure, new disease, new therapeutic activity, target identified, development continuing).

Events	**0–2 years**	**3–5 years**	**6+ years**	**TOTAL**
Additional launches	0.01	0.03	0.07	0.03
Additional registrations	0.01	0.03	0.06	0.03
Compounds identified	0.09	0.03	0.01	0.05
Development continuing	0.12	0.20	0.11	0.14
First launches	0.01	0.03	0.03	0.02
First registrations	0.01	0.03	0.03	0.02
Mechanism identified	0.04	0.02	0.02	0.03
Names granted	0.02	0.06	0.06	0.04
New chemical structure	0.20	0.07	0.05	0.12
New disease	0.13	0.18	0.22	0.17
New licensees	0.11	0.12	0.12	0.12
New patent applications	0.07	0.02	0.03	0.04
New therapeutic activity	0.10	0.10	0.09	0.10
Novel target reported	0.02	0.00	0.00	0.01
Orphan drug status granted	0.03	0.06	0.09	0.06
Target identified	0.03	0.02	0.01	0.02

Events	**0–2 years**	**3–5 years**	**6+ years**	**TOTAL**
Science related	0.70	0.62	0.50	0.62
Commercialization related	0.30	0.38	0.50	0.38

C. Data on Acquisitions

We collect acquisition data from three sources. We first extract all announced and completed M&As (with complete information on acquirer and target firms) and announced and effective dates from Thomson Reuters SDC Platinum. To supplement the SDC M&A data, we use Thomson Reuters RecapIQ (now Cortellis Deals Intelligence) data. RecapIQ documents deals in the biotechnology industry using information from company press releases, SEC filings, and company voluntary disclosures. Our third source of acquisition data is the SDC VentureXpert database, which covers mainly VC-backed, early stage start-ups. Using VentureXpert, we identify entrepreneurial companies that exited via an acquisition. However, since VentureXpert does not provide details on the acquirer and acquisition dates, we manually collect that information.

Armed with acquisition events compiled from multiple data sources, we then conduct a multistep cleaning process to ensure acquisition events are correctly linked to target and acquirer firms. We first standardize company names (for both acquirers and targets) and collect demographic information for each company. Second, since the same firm could appear in different databases under slightly different names, we create a unique firm identifier by grouping firms with highly similar standardized names and identical demographic characteristics (such as location). Third, using cleaned names of acquirers and targets and deal dates, we drop duplicate acquisition events (which appear possibly due to using multiple datasets). To the best of our knowledge, this combination provides the most comprehensive database on acquisitions in the pharmaceutical industry.[50]

We combine our acquisition database with the Pharmaprojects drug development data through a fuzzy matching algorithm combined with manual check. We consider a drug project acquired if the originator firm is acquired. In the end, for each drug in our database, we can identify whether it went through any acquisition event during its development life cycle and if it did, the acquirer, the timing of acquisition, and development activity in the years pre- and post-acquisition.

The merged drug development and acquisition data show active acquisition activities in our analytical sample, with 22 percent of drug projects having an acquisition recorded in our acquisition databases. As tabulated in table 1, the rate of acquisition is lower for drugs

[50]Each of the three data sources, SDC M&A Database, RecapIQ, and VentureXpert, independently contributes at least 10 percent of cases in the final database.

originated more recently. This pattern is likely because acquisitions often occur several years into drug development, and for more recent projects, some acquisitions may have not yet been realized at the time of data construction (i.e., right truncation).

D. Merging Drug Development and Acquisition Data with Patent Databases

In this section, we describe the process to merge drug development and acquisition data with USPTO patent databases through matching company names with assignee names in the USPTO patent database. To minimize potential problems introduced by the minor discrepancy between different versions of the USPTO database, we use both NBER and HBS patent databases to source patent assignee information. After this step, each company in the drug development and acquisition database will have its original name, standardized name, and a stem name; it is similar for USPTO assignees.

D.1. Name Standardization

We begin by standardizing company names in our drug development and acquisition database ("drug data" hereafter) described in Appendix B and assignee names from NBER and HBS patent databases using the name standardization algorithm developed by the NBER Patent Data Project. This algorithm standardizes common company prefixes and suffixes and strips names of punctuation and capitalization. It also isolates a company's stem name (the main body of the company name) excluding these prefixes and suffixes.

D.2. The Matching Procedure

With these standardized and stem company (assignee) names and demographic information provided by both the drug data and the USPTO, we merge the databases following the matching procedures below:

1. We match each standardized drug originator and owner name with standardized names from the NBER data and HBS data.
   (a) If an exact match is identified, we consider this as a "*successful match*." The company is removed from the set of names waiting to be matched on both sides.
   (b) Otherwise, we go to the next step.

2. Each stem drug originator and owner name is matched with stem names from the NBER data and HBS data.

   (a) If an exact match of stem names if identified, and the two companies are located in the same city and state OR the two companies are located in the same state and the earliest patenting year in NBER and HBS databases is later than the founding year in the drug data, we consider this as a "*successful match*." The company is removed from the set of names waiting to be matched on both sides.

   (b) If an exact match of stem names is identified, but the two companies do not satisfy the location and chronology criteria above, we consider this as a "*potential match*." The company is moved to a pool of firms waiting for manual checks.

   (c) Otherwise, we go to the next step.

3. For the remaining companies, each stem originator and owner name is matched with up to three close stem names from the USPTO data using a fuzzy matching method based on the Levenshtein edit distance.[51] The criterion is based on the length of the strings and the Levenshtein distance, and the threshold is determined through a random sampling procedure.

   (a) If the fuzzy matched pair is located in the same city and state OR the two companies are located in the same state and the earliest patenting year in NBER and HBS databases is later than the founding year in the drug data, we consider this as a "*potential match*."

   (b) Otherwise, the companies are categorized as "*failed to match*."

4. The "*potential matches*" set identified in the procedures above are reviewed by hand, incorporating information from both data sources, including full patent abstracts and company business descriptions.

   (a) Pairs confirmed as successful matches through the manual check are moved to the "*successful match*" set.

[51] The Levenshtein edit distance measures the degree of proximity between two strings and corresponds to the number of substitutions, deletions, or insertions needed to transform one string into the other one (and vice versa).

E. Clinical Trials

To supplement our main analyses, which use panel of all drug development events, we also examine the likelihood that a project continues to the next phase in the clinical trials process. In this section, we describe the process of creating the clinical trials dataset, outline the analysis, and present our clinical trial results.

E.1. Clinical Trials Data

To perform this supplementary analyses, we link the Pharmaprojects data with Pharma Intelligence's Trialtrove data on clinical trial phases at the project level. Drug clinical trials comprise three main phases: Phase I trials, which are small (20–100 healthy volunteers) and short and are intended to test safety; Phase II trials, which are larger (hundreds of affected patients), typically randomized control trials lasting up to two years and are intended to test efficacy; and Phase III trials, which are expanded versions of Phase II trials, involving hundreds or thousands of participants and typically lasting one to four years (US FDA, 2017). Following successful trials, firms may submit a New Drug Application (NDA) to the FDA, which then decides if, and under what conditions, the drug can be marketed to US patients. We use Trialtrove data to identify the initiation of clinical trials by phase, including the timing of trial initiation.

Notably, clinical trial phase data are widely available only from 1997 onward, when the US federal government first mandated the National Institutes of Health (NIH) to collect and make publicly available a comprehensive clinical trials database.[52] Therefore, we have comprehensive trial phase data only for projects first initiated after 1997. Within this limited sample, we identify projects for which we observe the start date of Phase I trials and track their progression, following prior studies that use progression through phases of clinical trials as a measure of project development (Krieger, 2017; Guedj and Scharfstein, 2004). We use trial progression as the dependent variable in these supplementary analyses.

In addition to providing robustness for our main results, analyzing progression through the clinical trial phases allows us to focus, albeit narrowly, on drugs in the exact same phase of clinical development and to examine progress to the next necessary phase. Focusing in this way helps

[52] More details on the timeline of publicly available clinical trials database can be found at http://www.clinicaltrials.gov.

to alleviate concerns that our main results are driven by differences in the stage of development across projects that might remain even after including various age, project, TC-MOA, and firm-related fixed effects. We treat the clinical trial analysis as supplementary evidence because our main analyses include a larger sample of projects and additional key development events besides trial starts (e.g., patent applications) and the panel structure allows for project-level fixed effects.

E.2. Evidence from Clinical Trials

In this analysis, we focus on the subsample of drugs that start Phase I clinical trials and are subsequently acquired and on projects started before 2011. We do this to ensure there is sufficient time to observe an acquisition and to give the analyzed projects enough time to enter Phase II trials. Using the following specification, we test whether drug projects acquired by firms with overlapping products are less likely to start Phase II trials than drug projects acquired by non-overlapping incumbents:

$$PhaseII_i = \beta \cdot I(Acquired)_i \times I(Overlap)_i + \alpha_{FE} + \varepsilon_i. \tag{14}$$

Table E1 presents the clinical trial regression results. We find that projects acquired by firms with overlapping products are 9.0 percentage points less likely to progress to Phase II than non-overlapping acquired projects (column 1). In terms of economic magnitude, this represents a decrease of 23.7 percent from the base rate of starting Phase II for acquired projects of 38 percent. Or, put in terms of project termination, 62 percent of non-overlapping acquired projects are stopped before starting Phase II versus 71 percent of overlapping acquired projects. Columns 2–4 examine how competition conditions these results. Akin to our main analyses, we find that the decreased likelihood of acquired overlapping projects progressing in clinical trials is concentrated in markets with low existing product market competition. We also replicate table E1 using "pipeline" competition (i.e., number of competing projects under development) in table E2 and find similar results to both table E1 and the pipeline version of the main competition analysis (Appendix table F8).

Table E1
Overlapping Acquisitions and Project Development: Clinical Trials

This table presents the likelihood of starting Phase II trials. An observation is a drug project that is acquired after starting Phase I clinical trials. We test whether drug projects acquired by firms with overlapping products are less likely to subsequently start Phase II trials than drug projects that are acquired by non-overlapping acquirers, using the following specification:

$$PhaseII_i = \beta \cdot I(Acquired)_i \times I(Overlap)_i + \alpha_{FE} + \varepsilon_i,$$

where the dependent variable $PhaseII_i$ is a dummy variable indicating whether drug i enters Phase II. $I(Acquired)_i$ indicates whether the drug (i) is acquired in Phase I. Note that $I(Acquired) = 1$ holds for every observation in this sample. $I(Overlap)$ is a dummy variable indicating whether the acquired drug overlaps with the portfolio of the acquirer. Standard errors are displayed in parentheses. ***, **, and * indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

	Phase II = 1			
	(1)	(2)	(3)	(4)
		Low Competition	High Competition	Interacted
I(Acquired) × Overlap	–0.090*	–0.287**	–0.065	–0.037
	(0.049)	(0.112)	(0.064)	(0.055)
I(Acquired) × Overlap × LowCompetition				–0.232**
				(0.109)
Observations	1,860	511	1,348	1,860
R-squared	0.548	0.815	0.548	0.554
Phase I start year FE	Y	Y	Y	Y
TC × MOA FE	Y	Y	Y	Y

Table E2
Overlapping Acquisitions and Project Development: Clinical Trials (Pipeline Competition)

This table presents the likelihood of starting Phase II trials, replicating the analysis in table E1. The key difference is the measure of competition in this table which is "pipeline competition." An observation is a drug project that is acquired after starting Phase I clinical trials. We test whether drug projects acquired by firms with overlapping products are less likely to subsequently start Phase II trials than drug projects that are acquired by non-overlapping acquirers, using the following specification:

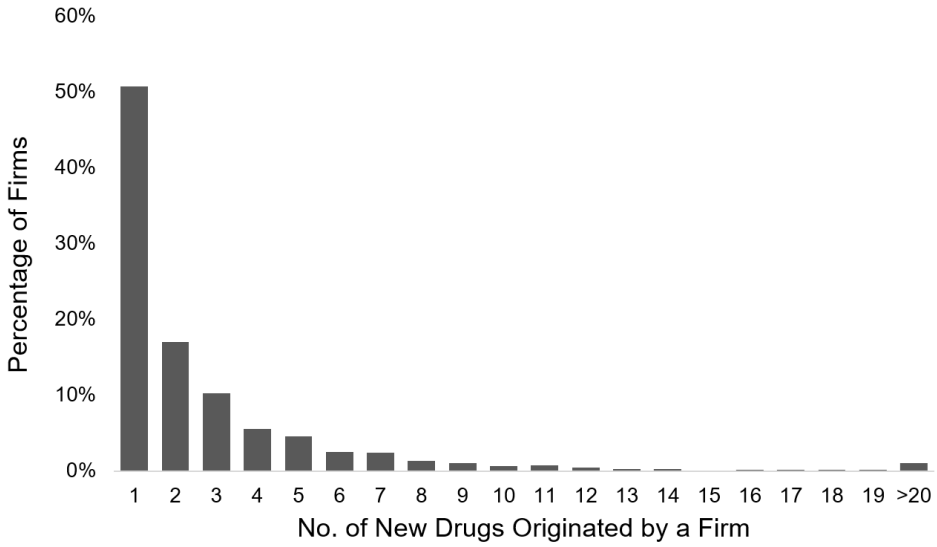
$$PhaseII_i = \beta \cdot I(Acquired)_i \times I(Overlap)_i + \alpha_{FE} + \varepsilon_i,$$

where the dependent variable $PhaseII_i$ is a dummy variable indicating whether drug i enters Phase II. $I(Acquired)_i$ indicates whether the drug (i) is acquired in Phase I. Note that $I(Acquired) = 1$ holds for every observation in this sample. $I(Overlap)$ is a dummy variable indicating whether the acquired drug overlaps with the portfolio of the acquirer. Standard errors are displayed in parentheses. ***, **, and * indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

	Phase II = 1			
	(1)	(2)	(3)	(4)
		Low Competition	High Competition	Interacted
I(Acquired) × Overlap	–0.090*	–0.260***	–0.085	–0.033
	(0.049)	(0.086)	(0.076)	(0.063)
I(Acquired) × Overlap × LowCompetition				–0.189*
				(0.103)
Observations	1,860	631	1,228	1,860
R-squared	0.548	0.836	0.518	0.561
Phase I start year FE	Y	Y	Y	Y
TC × MOA FE	Y	Y	Y	Y

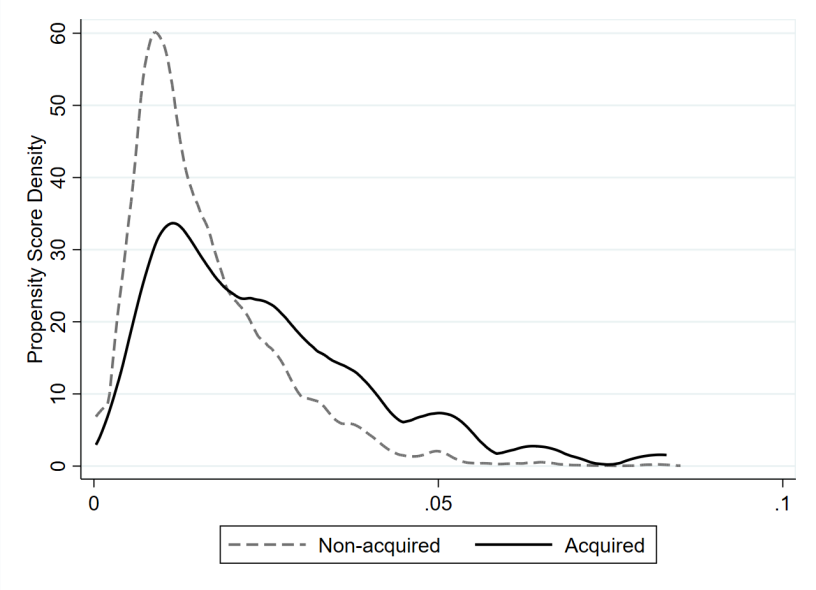
F. Additional Results

Figure F1. Firm Size (Number of New Drugs Originated) Distribution

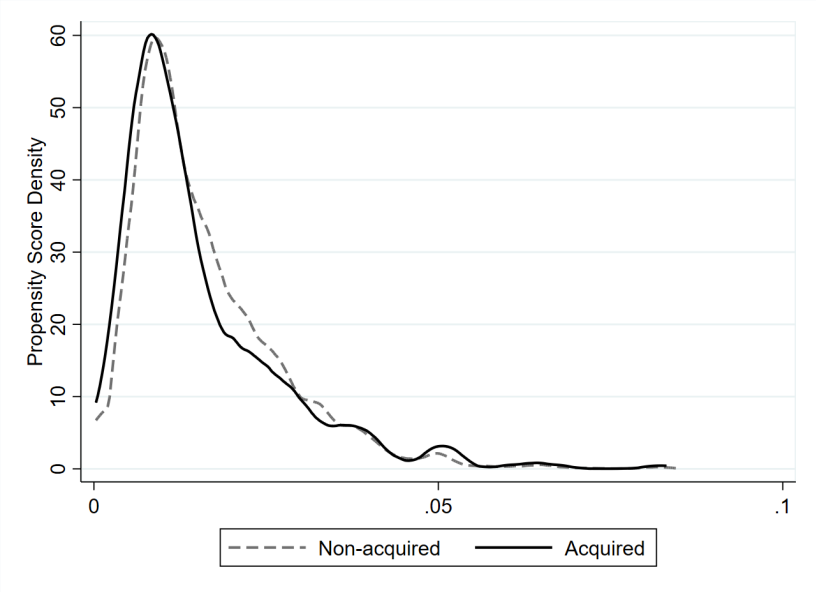


This graph plots the distribution of the number of new drugs originated by a company between 1989 and 2010. We assign a drug to a company if the company was the first to own the drug development project, but we do not assign the drugs that were obtained through acquisitions. The drug origination data are from the Pharmaprojects database.

Figure F2. Propensity Score Distribution: Acquired and Non-Acquired Drugs



(a) Unweighted



(b) Weighted

This graph plots the kernel density distribution of propensity scores for the acquired and non-acquired samples. Panel (a) uses the raw acquisition propensity, and Panel (b) uses the propensity score reweighting method described in section 4.2 and used for results in table 2 column 5.

Table F1
Overlapping Acquisitions and Project Development: Measures of Overlap

This table presents the development likelihood of drug projects using a drug-year panel sample. The empirical specification uses the following model:

$$\begin{aligned} Development_{i,t} = {} & \beta_1 \cdot I(Acquired)_i \times I(Post)_{i,t} \times I(OverlapTC-MOA)_i \\ & + \beta_2 \cdot I(Acquired)_i \times I(Post)_{i,t} \times I(OverlapTC)_i \\ & + \gamma_1 \cdot I(Acquired)_i \times I(Post)_{i,t} + \gamma_2 \cdot I(Acquired)_i \times I(OverlapTC-MOA)_i \\ & + \gamma_3 \cdot I(Acquired)_i \times I(OverlapTC)_i + \gamma_4 \cdot I(Acquired)_i + \alpha_{FE} + \varepsilon_{i,t}, \end{aligned}$$

where the dependent variable $Development_{i,t}$ is a dummy variable indicating drug i has a development event in year t. $I(Acquired)_i$ indicates drug i is acquired during the study period, and $I(Post)_{i,t}$ indicates whether the drug-year (i,t) observation is after the drug is acquired. $I(OverlapTC-MOA)_i$ is a dummy variable indicating the acquired drug overlaps with the product portfolio of the acquirer through the same TC and MOA. $I(OverlapTC)_i$ is a dummy variable indicating the acquired drug overlaps with the product portfolio of the acquirer through the same TC only (not same MOA). Standard errors clustered at the drug project level are displayed in parentheses. ***, **, and * indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)
	Development Event = 1			
I(Acquired) × I(Post) × Overlap (TC-MOA)	–0.052***	–0.037**	–0.036**	–0.051**
	(0.014)	(0.015)	(0.016)	(0.020)
I(Acquired) × I(Post) × Overlap (TC)	–0.046***	–0.018	–0.022	–0.036*
	(0.012)	(0.017)	(0.018)	(0.021)
I(Acquired) × I(Post)	–0.005	–0.012	–0.010	–0.013
	(0.007)	(0.009)	(0.010)	(0.012)
I(Acquired) × Overlap (TC-MOA)	0.009	0.007	0.034**	
	(0.008)	(0.009)	(0.013)	
I(Acquired) × Overlap (TC)	0.013*	–0.007	0.015	
	(0.007)	(0.010)	(0.013)	
I(Acquired)	–0.007	–0.001	–0.015	
	(0.005)	(0.006)	(0.013)	
Observations	143,569	143,569	143,569	143,569
R-squared	0.037	0.252	0.289	0.366
Vintage FE	Y	Y	Y	
Age FE	Y			
Age FE × TC × MOA		Y	Y	Y
Originator [Target company] FE			Y	
Project FE				Y

Table F2
Overlapping Acquisitions and Project Development: Standard Error Clustering

This table presents the likelihood of post-acquisition development events for drug projects using a drug-year panel sample, replicating columns 3 and 4 of table 2 but clustering the standard errors at the market (TC-MOA) (columns 1 and 2) and firm-market (columns 3 and 4) levels.

	Development Event = 1			
	(1)	(2)	(3)	(4)
I(Acquired) × I(Post) × Overlap	–0.029*	–0.041*	–0.029*	–0.041**
	(0.015)	(0.021)	(0.015)	(0.020)
I(Acquired) × I(Post)	–0.017**	–0.024**	–0.017*	–0.024**
	(0.009)	(0.010)	(0.009)	(0.011)
I(Acquired) × Overlap	0.026**		0.026**	
	(0.011)		(0.011)	
I(Acquired)	–0.011		–0.011	
	(0.012)		(0.012)	
Observations	143,569	143,569	143,569	143,569
R-squared	0.289	0.366	0.289	0.366
Vintage FE	Y		Y	
Age FE × TC × MOA	Y	Y	Y	Y
Originator [Target company] FE	Y		Y	
Project FE		Y		Y

Table F3
Overlapping Acquisitions and Project Development: Overlapping Definition

This table presents the likelihood of post-acquisition development events for drug projects using a drug-year panel sample, replicating table 2. The key difference is the definition of *Overlap*. In this table, an acquired drug is considered overlapping *only* if the acquirer has an existing project in the same TC-MOA as the target *and* the acquirer's project or product is further along in development (measured using age).

	Development Event = 1	
	(1)	(2)
I(Acquired) × I(Post) × Overlap	–0.044***	–0.073***
	(0.017)	(0.024)
I(Acquired) × I(Post)	–0.019***	–0.024***
	(0.007)	(0.009)
I(Acquired) × Overlap	–0.001	
	(0.010)	
I(Acquired)	0.002	
	(0.05)	
Observations	143,569	143,569
R-squared	0.255	0.370
Vintage FE	Y	
Age × TC × MOA FE	Y	Y
Project FE		Y

Table F4
Overlapping Acquisitions and Project Development: Therapeutic Class Fixed Effects

This table presents the likelihood of post-acquisition development events for drug projects using a drug-year panel sample, replicating table 2. The key difference is the use of age-TC level fixed effects instead of age-TC-MOA level fixed effects.

	Development Event = 1		
	(1)	(2)	(3)
I(Acquired) × I(Post) × Overlap	–0.030**	–0.034***	–0.036**
	(0.013)	(0.013)	(0.015)
I(Acquired) × I(Post)	–0.020***	–0.021***	–0.031***
	(0.006)	(0.006)	(0.007)
I(Acquired) × Overlap	0.006	0.016*	
	(0.008)	(0.009)	
I(Acquired)	–0.002	–0.000	
	(0.004)	(0.010)	
Observations	143,569	143,569	143,569
R-squared	0.067	0.107	0.186
Vintage FE	Y	Y	Y
Age FE × TC	Y	Y	Y
Originator [Target company] FE		Y	
Project FE			Y

Table F5
Overlapping Acquisitions and Project Development: Licensing

This table presents the likelihood of post-acquisition development events for drug projects using a drug-year panel sample, replicating table 2. The key difference is to include controls for any pre-acquisition licensing activity by including the variable, $I(Licensed)$, which indicates the drug has undergone a licensing event or codevelopment deal. To do so, we augment our data with comprehensive RecapIQ data on technology-related codevelopment and licensing deals.

	Development Event = 1		
	(1)	(2)	(3)
I(Acquired) × I(Post) × Overlap	–0.037**	–0.033***	–0.040**
	(0.013)	(0.014)	(0.019)
I(Acquired) × I(Post)	–0.020***	–0.017***	–0.024***
	(0.006)	(0.008)	(0.010)
I(Acquired) × Overlap	0.003	0.008*	
	(0.008)	(0.009)	
I(Acquired)	–0.003	–0.005	
	(0.004)	(0.005)	
I(Licensed)	0.006**	0.006*	0.015
	(0.003)	(0.003)	(0.009)
Observations	143,569	143,569	143,569
R-squared	0.038	0.256	0.370
Vintage FE	Y	Y	
Age FE	Y		
Age × TC × MOA FE		Y	Y
Project FE			Y

Table F6
Overlapping Acquisitions and Project Development: Matched Non-Acquired Drugs

This table presents the likelihood of not experiencing any development event, replicating table 3. The key difference is that this table includes drugs that are not acquired, whereas table 3 uses acquired drugs. The reason for using only acquired drugs in table 3 is because that analysis uses acquisition events to study differences in (pre- and) post-acquisition likelihood of "never developed."
To run the same analyses as in table 3 but also to include non-acquired drugs, we matched acquired projects to non-acquired projects (matched based on pre-acquisition development rates up to the acquired project's acquisition age). We randomly selected three non-acquired projects among those with the same development rates for each acquired project and created "pseudo acquisition" events for non-acquired projects using the matched acquired projects. In the regressions, $I(PseudoAcquired) \times I(Post)$ captures the pseudo acquisition event for all matched, non-acquired projects, and $I(Acquired) \times I(Post) \times Overlap$ captures the coefficient of interest.

	No Development = 1			
	(1)	(2)	(3)	(4)
I(Acquired) × I(Post) × Overlap	0.102***	0.105***	0.120***	0.139***
	(0.025)	(0.030)	(0.041)	(0.038)
I(Acquired) × I(Post)	0.033**	0.024	0.045*	0.013
	(0.015)	(0.018)	(0.025)	(0.022)
I(Pseudo Acquired) × I(Post)	0.274***	0.332***	0.355***	0.369***
	(0.008)	(0.010)	(0.014)	(0.011)
I(Acquired) × Overlap	–0.023	–0.017	–0.035	
	(0.015)	(0.015)	(0.028)	
I(Acquired)	–0.002	–0.000	–0.001	
	(0.008)	(0.011)	(0.018)	
Observations	27,993	27,993	27,993	27,993
R-squared	0.074	0.265	0.368	0.442
Vintage FE	Y	Y	Y	
Acq age FE	Y	Y		
TC × MOA		Y		Y
Acq age × TC × MOA FE			Y	
Project FE				Y

Table F7
Overlapping Acquisitions and Industry-Level Project Development

This table presents TC-MOA-year level analysis drug development of "control" projects as it relates to acquisition activity in the focal market. The sample is drug projects that are neither acquired by an overlapping acquirer nor belonging to the acquirer firm. The analysis investigates if acquisitions of potential competitor drugs increase subsequent development of the non-acquired projects. The empirical specification uses the following model:

$$DevelopmentRate_{j,t} = \gamma \cdot (\#OverlappingAcquisitions)_{j,t} + \alpha_j + \varepsilon_{j,t},$$

where the dependent variable $DevelopmentRate_{j,t}$ is the average number of development events for drug projects in the TC-MOA j in year t. $(\#OverlappingAcquisitions)_{j,t}$ is the number of overlapping acquisitions in the TC-MOA j in year t. ***, **, and * indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

	(1)	(2)	(3)
	Non-Acquired Project Development		
Number of overlapping acquisitions	–0.030***		
	(0.007)		
ln(Number of overlapping acquisitions)		–0.082***	
		(0.014)	
Asinh(Number of overlapping acquisitions)			–0.095***
			(0.016)
Observations	70,139	70,139	70,139
R-squared	0.183	0.183	0.183
TC × MOA FE	Yes	Yes	Yes

Table F8
Overlapping Acquisitions and Project Development: Pipeline Competition

This table presents the development likelihood of drug projects replicating the table 4 analyses. The key difference is the measure of competition in this table is "pipeline competition." The empirical specification uses the following model:

$$Development_{i,t} = \beta \cdot I(Acquired)_i \times I(Post)_{i,t} \times I(Overlap)_i + \gamma_1 \cdot I(Acquired)_i \times I(Post)_{i,t} + \gamma_2 \cdot I(Acquired)_i \times I(Overlap)_i + \gamma_3 \cdot I(Acquired)_i + \alpha_{FE} + \varepsilon_{i,t},$$

where the dependent variable $Development_{i,t}$ is a dummy variable indicating drug i has a development event in year t. $I(Acquired)_i$ indicates drug i undergoes an acquisition event, and $I(Post)_{i,t}$ indicates the drug-year (i,t) observation is after the drug is acquired. We count the number of firms with a drug or drug project that is in the same market (same TC-MOA) as the focal drug. The analysis predicts likelihood of development across all projects in a project-year panel. Drug development projects are categorized into high and low competition by the median of competition measures, which is measured using the number of projects in the pipeline. In column 3 we present results in which we interact $I(Acquired)_i \times I(Post)_{i,t} \times I(Overlap)_i$ with the dummy indicating low competition. Standard errors clustered at the drug project level are displayed in parentheses. ***, **, and * indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

	Development Event = 1		
	(1)	(2)	(3)
	Low	High	Interacted
I(Acquired) × I(Post) × Overlap	–0.083***	–0.012	–0.012
	(0.030)	(0.026)	(0.027)
I(Acquired) × I(Post) × Overlap × LowCompetition			–0.071*
			(0.040)
Observations	72,782	70,787	143,569
R-squared	0.425	0.348	0.385
Age FE × TC × MOA	Y	Y	Y
Project FE	Y	Y	Y