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ABSTRACT

We study how the inventive capability of a firm conditions its participation in a division of innovative labor. Capable firms are, by definition, able to invent; for them, external inventions substitute for their own R&D. However, external knowledge is an input into internal invention, and thus, more valuable to firms with inventive capability. Using a simple model of innovation and imitation, we explore how inventive capability affects a firm's R&D investments, and thus whether and how it innovates, imitates, or does neither. Further, we study how these outcomes are conditioned by the supply of external knowledge as well as the supply of external inventions. In an advance over the literature, we treat firm inventive capability as unobserved, and use a latent class multinomial model to infer its value. Using a recent survey of product innovation and the division of innovative labor among US manufacturing firms, we find that high capability firms tend to use internal, rather than externally generated inventions, to innovate, and they use external knowledge to enhance their internal inventive activity. By contrast, lower capability firms are more likely to introduce "me-too" or imitative products, and when they innovate, are more likely to rely on external sources of inventions. Our findings suggest the successful pursuit of R&D-led growth depends both on firm inventive capability and the external knowledge environment.

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1 Introduction

The large, technologically self-sufficient firm is no longer (and perhaps never was) the key driver of economic growth. Indeed, recent evidence suggests that nearly half of the product innovations introduced by American manufacturing firms originate from external sources, Arora et al. (2016). If so, the innovative performance of the economy relies upon a "division of innovative labor" (Jewkes et al., 1958; Cassiman & Veugelers, 2006; Arora et al., 2016). In this division of labor, one can coarsely distinguish between two important stages. First, an invention results in either a new product or an improvement upon an existing product. Second, either the inventor or another firm will *innovate*, that is, commercialize the invention. These two stages involve different types of firm-capabilities, including inventive and commercialization capabilities, where *inventive capability* can be thought of as the upstream technical expertise and functions that allow firms to generate new products, or improve existing products.[1] In this paper, we assess how innovators uses different forms of external knowledge, and whether they compete on the basis of their own inventions or the use of others' inventions.

Our contributions to the literature are twofold. First, we advance understanding of the role of firm capabilities in the innovation process by showing that firms' inventive capabilities complement externally available knowledge, but substitute for externally available inventions. These findings rationalize the potentially conflicting findings in the innovation literature around whether firm capabilities complement or substitute for external knowledge. The key is to distinguish external raw knowledge from more fully formed inventions; external knowledge inputs can therefore both substitute and complement the focal firm's inventive capability. We also find that firm size complements the innovative performance advantage associated with inventive capability, which is consistent with size scaling the expected payoffs to both innovation and imitation (Cohen & Klepper, 1996).

[1] In contrast, a firm's commercialization capability reflects its abilities to develop, manufacture, market and sell the new products that derive from inventions.

Our second contribution is methodological. By applying a finite mixture model approach to treat inventive capability as an unobserved, latent variable, we contribute to the strategy and innovation literatures by obviating the concerns over endogeneity that have plagued the empirical literature on the role of firm capabilities. Further, unlike most prior uses of finite mixture models, we use our predictions about the interactions between capability, external invention supply, and size to interpret our latent classes.

As a basis for our empirical analysis, we develop a simple model in which firms choose whether to commercialize a new product (based either on an internally generated idea or an external invention), or not. In a prior stage, firms choose their R&D investments, which enhance the value of internally generated ideas. Some of the new products are new to the market, and are innovative. Others are similar to existing products, and are perhaps improvements or simply differentiated from them in some respects. We call these imitative. Though both types can arise from internal R&D, we assume that innovations are more responsive to R&D investments than are imitations. We model capability as reducing the marginal cost of R&D, so that all else equal, high capability firms have higher R&D.

We distinguish two different forms of external innovation inputs: 1) external "raw" knowledge flows—that we will simply call "knowledge"—that increase the productivity of internal R&D, and 2) externally available inventions that firms can acquire and commercialize. The model implies that both high and low capability firms will innovate more when located in environments rich in knowledge and inventions. The prediction differs, however, depending on whether the location is rich in inventions or rich in knowledge. In locations rich in external inventions, low capability firms will innovate more than otherwise by acquiring inventions. Firms with greater inventive capabilities, however, are less likely to capitalize on such external inventions because they have a more attractive "inside option". But in the presence of more external knowledge, increased R&D efficiency disproportionately benefits high capability firms, leading to greater internal invention.

Our model also yields more nuanced predictions that we empirically examine. For instance, it suggests that size and inventive capability are complements, in that innovation increases faster with size in higher capability firms. Further, the model suggests that because low capability firms do less R&D, their new product introductions (i.e., innovation and imitation) is less responsive to external knowledge than is the case for high capability firms. On the other hand, low capability firms are more responsive to the supply of external ideas than are high capability firms.

Our empirical analysis uses a survey of U.S. manufacturing firms for the period 2007 to 2009 (Arora et al., 2016) that focuses on innovation and the division of innovative labor, including the sourcing of invention. The survey samples all manufacturing firms, not just those with prior R&D spending or patents, allowing us to explore innovation-related choices for a wide spectrum of firms. Our sample distinguishes our research from much of the literature that explores the use of external sources by innovators or R&D performing firms as surveyed by Vivas & Barge-Gil (2015), or only firms in industries where innovation is the basis of competition, e.g., pharmaceuticals or semiconductors (Ceccagnoli et al., 2010; Fabrizio, 2009). We link the survey data to other datasets, including patent data, and to measures of the local knowledge environment, and exploit geographic and industry-specific variation to construct measures of the external supply of inventions and knowledge (Jaffe, 1986; Feldman, 1993; Delgado et al., 2014; Porter, 1998; Carlino & Kerr, 2015).

Note that we are not estimating the causal impact of external knowledge on innovation. Instead, we seek to test whether the patterns of association between the external knowledge environment and the rate and composition of innovation differ between high and low capability firms as predicted by our simple model. We do not directly measure inventive capability using empirical proxies such as prior patents, R&D, innovation, or sales. Instead, we treat firm capability as an unobserved latent variable by using a semi-parametric finite-mixture model approach, more commonly used in the marketing literature (e.g., McLachlan & Peel (2004); Kamakura & Russell (1989); Colombo & Morrison (1989)).[2] We leverage theory to

[2]FMM models are similar to some types of unsupervised machine learning. A multinomial logit relates characteristics to outcomes, and the coefficients can differ for firms of different capabilities (latent types).

identify the latent class associated with higher inventive capability, and use the predicted firm-specific probability of belonging to that latent class as a measure of the firm's inventive capability.

To prefigure our empirical results, we observe that firms with greater inventive capabilities are more likely to both innovate and imitate.[3] Consistent with prior findings, we find that location in a rich knowledge environment—rich in either "raw" knowledge or more fully developed inventions—has a positive relationship on average with innovation and imitation.[4] But firms benefit in different ways depending on their inventive capability. Less capable firms build on the inventions of others, often to imitate, whereas more capable firms use external knowledge to enhance their internal inventions.

Section 2 below provides a brief discussion of the related literature. In section 3, we develop our theoretical model and in section 4 analyze how firms' inventive capabilities condition their use of the external knowledge environment, and thereby shape the their innovative activity. Our data are described in section 5. In section 6 we use a finite-mixture model to estimate our measure of inventive capability, and examine how the relationship between the external knowledge environment and innovation differs by firm inventive capability. In section 7, we examine the relationship between inventive capability and the use of outside knowledge and inventions. In section 8 we explore how capability is related to performance. Section 9 summarizes our results, discusses their implications for the related literature, and offers some practical implications for management.

Each observation is assigned a starting probability, sometimes called the prior probability, of originating from a firm with a given capability level, which leads to a different set of coefficient estimates relating observable characteristics such as age and size to outcomes such as innovation. Conditional on the actual outcome, there is a posterior probability of a given observation originating from a firm with a particular capability level. In turn, this posterior probability serves as the basis for the next round of estimates. The process continues until the prior and posterior converge.

[3]Some me-too products can be very profitable. Examples include Samsung's introduction of its Galaxy smartphone line subsequent to Apple's introduction of the iPhone, or Warner Lambert's development of Lipitor (subsequently commercialized by Pfizer) after Merck's commercial introduction of the first statin, Mevacor (lovastatin).

[4]This is consistent with findings both from the markets for technology literature (West & Bogers, 2014; Arora et al., 2001a) that focuses on external sourcing of invention as the key driver, and findings from geography of innovation literature (Audretsch & Feldman, 2004) that focuses on knowledge spillovers and internal invention as the key driver.

2 Background

To understand the contribution of this paper to the literatures on innovation and firm strategy, consider that the literature on R&D spillovers and the literature on markets for technology largely posit opposite relationships between a firm's internal capabilities and external knowledge. When emphasizing the role of absorptive capacity, the literature on spillovers highlights the complementarity between a firm's capability and external knowledge: To use external knowledge effectively, firms need to engage in internal invention. In contrast, the literature on markets for technology argues that external inventions substitute for internal capability. These findings lead to an apparent puzzle, that the firms with the most to gain from participating in a division of innovative labor are also the least able to do so. They also have very different predictions for competitive dynamics. If internal capability and external knowledge are complements, then more capable firms' use of external knowledge will reinforce their competitive advantage. If they are substitutes, then external knowledge will have a leveling effect. While more apparent than real, this puzzle reflects a gap in our understanding of the relationship between capabilities and external knowledge. There are two reasons for this gap. One is conceptual, reflecting a lack of specificity around characterization of external knowledge. The other is methodological, reflecting the challenges associated with the measurement of firm capabilities.

Scholars have typically not distinguished between the knowledge flows that provide the grist for invention versus inventions themselves (Griliches, 1992; Arora et al., 2016), and have implicitly focused on only one or the other form of external inputs to innovation. For example, the literature on R&D spillovers and absorptive capacity (Cohen & Levinthal, 1990; Volberda et al., 2010) and the related literature on the geography of innovation (Audretsch & Feldman, 2004; Feldman & Pentland, 2003; Feldman, 1993) have focused largely on the knowledge flows that are inputs to firm R&D. In contrast, those studying markets for technology (Arora et al., 2001a; Cassiman & Veugelers, 2006; Veugelers & Cassiman, 1999) have focused on external inventions which can substitute for internal R&D. By not distinguishing between knowledge flows and inventions, the literature also implicitly conflates different stages in the innovative process. Whereas the literature on R&D spillovers has implicitly focused on invention, the literature on markets for technology has focused on how inventions are commercialized. We explicitly distinguish between knowledge and invention and empirically confirm that whereas external knowledge complements inventive capability, external inventions substitute for it.

A second gap in the literature on the impact of firm capabilities on the use of external knowledge concerns the measurement of firm capabilities themselves. Prior studies of the effect of capabilities on the use of external knowledge have typically employed observables such as R&D or patents as proxies for firms' technical capabilities. This is a problem to the extent that innovative activity such as R&D is itself endogenous with respect to the external knowledge environment. Using patents or past innovation creates further potential biases. While some firms may not innovate despite some underlying capability, others may innovate in the absence of such capability. In this paper, we will treat capability as unobserved. Specifically, we treat it as a latent variable with the use of a finite-mixture model, as described below, and thus avoid the endogeneity tied to the use of R&D or patenting as measures of inventive capability in studies of the effect of capability on innovative performance.

3 Model

To study the link between external supply of knowledge and inventions and inventive capability in firm innovation outcomes, we develop a simple model of invention and innovation. Innovation is distinguished from imitation based on whether the product is new to the market (an "innovation") or simply new to the firm (an "imitation"). Further, we distinguish internal and external sources of the idea or invention underpinning the innovation or imitation.

Suppose there are 5 outcomes, indexed by j, with corresponding payoffs:

1. internal innovation (new product based on an internally generated idea or invention), denoted by subscript in: $q(v_{in} + \epsilon_{in})$
2. internal imitation (me-too product based on an internally generated idea or invention)

denoted by subscript im: $q(v_{im} + \epsilon_{im})$

3. external innovation (new product based on external idea or invention) denoted by subscript xn: $q(v_{xn} + \epsilon_{xn})$

4. external imitation (me-too product based on external idea or invention) denoted by subscript xm: $q(v_{xm} + \epsilon_{xm})$

5. none: $q(v_o + \epsilon_o)$

Note that we have scaled the payoffs by firm size, q, which is consistent with the fixed cost spreading logic of Cohen & Klepper (1996) whereby payoffs from innovation are proportional to firm size. Thus $v_j + \epsilon_j$ can be interpreted as the unit payoff from the j^{th} outcome. The v_j are the expected unit payoff associated with the j^{th} outcome, and ϵ_j, which represent stochastic departures from the expected payoff are assumed to be *iid* with type 1 extreme value distribution, with mean 0, and variance of ϵ_j is $\pi^2/6$.[5] Each firm chooses the outcome with the highest realized payoffs. In other words, in our model, scale does not directly affect innovation outcomes. However, as we will show below, size affects the innovation outcome through its effect on the choice of optimal internal R&D effort, R.

The firm maximizes $\Pi - C(R;\delta)$, where Π is the expectation of the best available outcome, so that $\Pi = E_\epsilon\{Max_j q\{v_j + \epsilon_j\}\} = qln\sum_j exp(v_j)$, and $C(R;\delta)$ is the cost of internal R&D, which depends on inventive capability, δ, such that the marginal cost $C'(R) = \frac{\partial C}{\partial R}$, decreases with δ.

The first order condition for an interior maximum is:

$$\frac{\partial \Pi}{\partial R} - C'(R) = 0 \tag{1}$$

The probability of outcome i, is denoted by $\psi_i = \frac{exp(v_i)}{\sum_j exp(v_j)}$. Note that ψ_i increases with v_i, and therefore anything that increases v_i will also increase ψ_i.

[5]For simplicity, we set the location parameter to 1 which gives us the variance as above.

Equation 1 can be rewritten as

$$q\sum_j \psi_j \frac{\partial v_j}{\partial R} - C'(R) = 0 \tag{2}$$

That is, the weighted average of the marginal product of R should be equal to its marginal cost, where the weights are the shares of each outcome (i.e., the probability that each payoff is realized). From now on, we normalize $v_0 = 0$, so that payoffs are interpreted relative to the payoff from doing nothing.

We assume that the second order condition for an interior maximum holds

$$\frac{\partial^2 \Pi}{\partial R^2} - C'' < 0 \tag{3}$$

The payoffs of the innovation outcomes depend upon the firm's characteristics, their internal R&D effort R, and environmental factors such as the supply of external inventions, s, and the stock of relevant knowledge, k. Specifically, we assume that

1. v_{in} and v_{im} increase with internal R&D effort R but are independent of the supply of external inventions s;

2. v_{xn} and v_{xm} increase with the supply of external inventions s but are independent of R.

3. Knowledge k reduces the marginal cost of R&D, i.e., $\frac{\partial C'}{\partial k} < 0$.

We further assume that internal R&D effort matters more for innovation than imitation. Specifically, we assume that

$$\begin{gathered}\frac{\partial v_{in}}{\partial R} \geq \frac{\partial v_{im}}{\partial R} \\ \frac{\partial ln(v_{in})}{\partial ln(R)} = \beta_{in} > \frac{\partial ln(v_{im})}{\partial ln(R)} = \beta_{im}\end{gathered} \tag{4}$$

These assumptions imply that internally generated ideas are more valuable if there is higher R, especially for innovative products rather than imitative products. They further imply that R is higher if the stock of knowledge, k, is higher. Finally, the payoff from external ideas is greater if the quality and quantity of external ideas, s, is higher.

3.1 Optimal R&D effort

We now show that optimal internal R&D effort, R (i.e,. the R implied by [1]) increases with capability, δ and with firm size q. First, we can show optimal R&D effort increases with capability. From [2], we can see that

$$\frac{\partial R}{\partial \delta}\left(\frac{\partial^2 \Pi}{\partial R^2} - C''\right) = \frac{\partial C'}{\partial \delta} \tag{5}$$

which implies $\frac{\partial R}{\partial \delta} \geq 0$ because $\frac{\partial C'}{\partial \delta} \leq 0$ and $\frac{\partial^2 \Pi}{\partial R^2} \leq 0$.

Second, optimal R&D effort increases with firm size. From [2], we can see that

$$\begin{aligned} \left(\frac{\partial^2 \Pi}{\partial R^2} - C''\right) dR &= -\left(\sum_j \phi_j \frac{\partial v_j}{\partial R}\right) dq \\ \frac{\partial R}{\partial q} &= -\frac{C'(R)}{q} \frac{1}{\left(\frac{\partial^2 \Pi}{\partial R^2} - C''\right)} > 0 \end{aligned} \tag{6}$$

In addition, we assume that the elasticity of R with respect to q is constant. That is, we assume that $\frac{q}{R}\frac{\partial R}{\partial q}$ is constant, i.e. θ. If $\theta = 1$, it would imply a constant proportion of sales are spent on internal R&D. A constant elasticity implies size-proportional R&D intensity, which, comfortingly, matches with existing empirical findings (Cohen, 2010). Because of the highly non-linear form of [6], this assumption simplifies our analyses.

Further, note that ψ_{in} increases with q. Formally,

$$\begin{aligned}
\psi_{in} &= \frac{exp(v_{in})}{\sum_j exp(v_j)} \\
\frac{\partial \psi_{in}}{\partial q} &= \frac{\partial R}{\partial q}\psi_{in}\left(\frac{\partial v_{in}}{\partial R} - \psi_{in}\frac{\partial v_{in}}{\partial R} - \psi_{im}\frac{\partial v_{im}}{\partial R}\right) \\
&\geq \frac{\partial R}{\partial q}\psi_{in}\frac{\partial v_{in}}{\partial R}\left(1 - \psi_{in} - \psi_{im}\right) \geq 0
\end{aligned}$$

4 Linking the model to the empirical analysis

In our data, we cannot empirically distinguish between internal and external sources for imitation. Therefore we collapse our five innovation outcomes into three: innovation, imitation, and none. If the unit payoff associated with innovation is $v_n + \epsilon_n$, then $v_n + \epsilon_n = Max\{v_{in} + \epsilon_{in}, v_{xn} + \epsilon_{xn}\}$. Following from the IIA (independence of irrelevant alternatives) property of the multinomial logit, $v_n = ln\left(exp(v_{in}) + exp(v_{xn})\right)$.[6] We define the expected unit payoff from imitation, v_m analogously as $v_m = ln\left(exp(v_{im}) + exp(v_{xm})\right)$.

4.1 Innovation, Imitation, and Capability

We use the model to generate predictions about the relationship between innovation, imitation, and capability. More precisely, we analyze the effect of capability, size, external invention, and knowledge, on the payoffs associated with innovation and imitation.

4.1.1 Innovation and capability

The average payoff from innovation, v_n, is higher for high capability firms.

$$\begin{aligned}
\frac{\partial v_n}{\partial \delta} &= t_n \delta \frac{\partial v_{in}}{\partial R}\frac{\partial R}{\partial \delta} \geq 0 \\
\text{where } t_n &= \frac{exp(v_{in})}{exp(v_{in}) + exp(v_{xn})}
\end{aligned} \tag{7}$$

A related implication of the model is that the average payoff from imitation, v_m, is higher

[6]For formal proof, see Anderson et al. (1992), pages 58-62.

for high capability firms. Formally, let $t_m = \frac{exp(v_{im})}{exp(v_{im})+exp(v_{xm})}$. The derivative of v_m w.r.t δ is given by

$$\frac{\partial v_m}{\partial \delta} = t_m \frac{\partial R}{\partial \delta} \frac{\partial v_{im}}{\partial R} \geq 0 \tag{8}$$

We can summarize [8] and [7] in the following:

Proposition 1 Innovation and imitation are higher for high capability firms than low capability firms

4.1.2 Innovation, Imitation and Capability

The relative share of innovation and imitation is given by $\frac{\psi_n}{\psi_m} = \frac{exp(v_{in})+exp(v_{xn})}{exp(v_{im})+exp(v_{xm})}$. This ratio increases with R if $\frac{exp(v_{in})}{exp(v_{im})} > \frac{exp(v_{xn})}{exp(v_{xm})}$.[7] Note that $\frac{exp(v_{in})}{exp(v_{im})}$ increases with R whereas $\frac{exp(v_{xn})}{exp(v_{xm})}$ is independent of R. In other words, the higher the capability (and hence, the higher is R), the more likely that increases in capability will increase the ratio of innovation to imitation.

Intuitively, as capability increases, the value of internal innovation increases faster than imitation. What we then expect is that high capability firms will use internal inventions and innovate. Low capability firms, on the other hand, will largely rely on external sources, and more typically to imitate rather than innovate. This illuminates a core feature of a division of innovative labor: capabilities condition not just whether a firm will source externally but also if they innovate or imitate (or do not introduce new products at all). While we cannot fully test this since we don't know the source of invention underpinning imitation, our theory illuminates this feature of the division of innovative labor, which has not been discussed in prior literature.

4.2 Capability and innovation response to size

The foregoing propositions are quite straightforward and intuitive: more capable firms are more likely to innovate or imitate than not commercialize a new product even when allowing

[7] The condition is sufficient for the result to hold.

for externally sourced inventions. However, our next prediction provides some nuanced logic that emerges from the model and is less obvious without the formal structure of the model.

Recalling that $t_n = \frac{exp(v_{in})}{exp(v_{in})+exp(v_{xn})}$ is the share of innovations based on internal inventions, the impact of firm size q on the payoff from innovation is given by:

$$\begin{aligned}\frac{\partial v_n}{\partial q} &= t_n \frac{\partial v_{in}}{\partial R}\frac{\partial R}{\partial q} \\ &= t_n \frac{v_{in}}{q}\beta_{in}\theta\end{aligned} \tag{9}$$

This implies that size increases the likelihood of innovation. A analogous result holds for imitation. How does this result differ across firms of different inventive capability? First, note that as δ increases, this results in higher R, thereby increasing v_{in}, which will also imply an increase in t_n, the share of innovations based on internal inventions. It follows that $\frac{\partial v_n}{\partial q}$ is higher for higher δ. More formally, the impact of capability on the relationship between size and innovation is given by :

$$\frac{\partial^2 v_n}{\partial q \partial \delta} = \frac{\beta_{in}\theta}{q}\left(t_n \frac{\partial v_{in}}{\partial R}\frac{\partial R}{\partial \delta} + v_{in}\frac{\partial t_n}{\partial R}\frac{\partial R}{\partial \delta}\right) > 0 \tag{10}$$

where β_{in} is the elasticity of the internal innovation payoff v_{in} with respect to R

An analogous argument establishes that the response of v_m to an increase in q is greater for higher capability firms. Proposition 2 below summarizes this.

Proposition 2: Innovation and imitation increase more quickly with size for high capability than low capability firms.

4.3 Capability and response to supply of external inventions, s

We next examine how capability interacts with the supply of external invention. Note that external inventions increase the payoff from innovation. Formally

$$\frac{\partial v_n}{\partial s} = \left(t_n \frac{\partial v_{in}}{\partial s} + (1-t_n)\frac{\partial v_{xn}}{\partial s}\right) = (1-t_n)\frac{\partial v_{xn}}{\partial s} \geq 0 \tag{11}$$

Using a similar logic, the imitation payoff also increases with the supply of external inventions. In [11] the higher is the share of innovation based on internal inventions, the lower is $1-t_n$. Therefore, innovation by low capability firms is more responsive to the supply of external inventions. Intuitively, higher capability firms rely more on internally generated inventions, which substitute for external ones. Formally:

$$\frac{\partial^2 v_n}{\partial s \partial \delta} = -\left(\frac{\partial t_n}{\partial R}\frac{\partial R}{\partial \delta}\right)\frac{\partial v_{xn}}{\partial s} < 0 \tag{12}$$

A similar argument yields the result that imitation by high capability firms is less responsive to the supply of external inventions than imitation by high capability firms.

Proposition 3: Innovation and imitation increase more quickly with the supply of external inventions for low than high capability firms.

4.4 Capability and response to knowledge k

Capability also conditions the response to external knowledge. An increase in the supply of knowledge increases R and hence increases the payoff from internally generated inventions. This implies that a higher k will lead to more innovation and imitation.

$$\frac{\partial v_n}{\partial k} = \frac{\partial R}{\partial k}\left(t_n \frac{\partial v_{in}}{\partial R} + (1-t_n)\frac{\partial v_{xn}}{\partial R}\right) = t_n \frac{\partial v_{in}}{\partial R}\frac{\partial R}{\partial k} \geq 0 \tag{13}$$

If, in addition, we assume that capability and external knowledge are complements, in the sense that the elasticity of R&D with respect to capability (weakly) increases with external knowledge, i.e., $\theta_i \equiv \frac{\partial Ln(R)}{\partial Ln(\delta)}$ increases with k, then, innovation and imitation by higher capability firms will be more responsive to external knowledge than lower capability firms.

To see this, recall from equation [7] that

$$\begin{aligned}\frac{\partial v_n}{\partial \delta} &= t_n \delta \frac{\partial v_{in}}{\partial R}\frac{\partial R}{\partial \delta} \\ &= t_n v_{in} \beta_{in} \theta_i\end{aligned} \tag{14}$$

where β_{in} is the elasticity of v_{in} with respect to R.

Note that t_n increases with k. Further, v_{in} increases with R and therefore, increases with k. As long as θ_i does not decrease with k, it is sufficient to yield the result that $\frac{\partial^2 v_n}{\partial\delta\partial k} \geq 0$. A similar argument implies that imitation by high capability firms is more responsive to the supply of external knowledge than imitation by low capability firms. Concretely,

$$\frac{\partial v_m}{\partial \delta} = t_m v_{im} \beta_{im} \theta_i \tag{15}$$

Similar to [14], t_m increases with k, v_{im} increases with R and therefore with k, and θ_i does not decrease with k, which is sufficient for the result: $\frac{\partial^2 v_m}{\partial\delta\partial k} \geq 0$.

Proposition 4: Innovation and imitation increase more quickly with the supply of external knowledge for high than low capability firms.

In sum, we expect that: high capability firms innovate and imitate more than low capability firms; size will increase innovation and imitation more quickly for higher capability firms; external supply of inventions will increase innovation and imitation more for low capability firms; and external supply of knowledge will affect innovation and imitation positively for both high and low capability firms. We will use these predictions to interpret our latent class analyses below.

4.5 Capability and external invention supply

For innovating firms, the share of innovation from internal inventions is t_n. This share increases with δ:

$$\begin{aligned}\frac{\partial t_n}{\partial \delta} &= \frac{exp(v_{in})exp(v_{xn})}{(exp(v_{xn}) + exp(v_{in}))^2}\frac{\partial v_{in}}{\partial \delta} \\ &= t(1-t)\frac{\partial v_{in}}{\partial \delta} \geq 0\end{aligned} \tag{16}$$

Further, and unsurprisingly, the share of innovation from internal inventions t_n decreases with s.

$$
\begin{aligned}
\frac{\partial t_n}{\partial s} &= -\frac{exp(v_{in})exp(v_{xn})}{(exp(v_{xn}) + exp(v_{in}))^2}\frac{\partial v_{xn}}{\partial s} \\
&= -t(1-t)\frac{\partial v_{xn}}{\partial s} \leq 0
\end{aligned} \tag{17}
$$

Proposition 5: The share of external invention increases with s and will be higher for lower capability firms than high capability firms.

4.6 Size, capability, and the source of inventions for innovation

For innovating firms, the share of internal inventions increases with size, q:

$$
\begin{aligned}
\frac{\partial t_n}{\partial q} &= \frac{exp(v_{in})exp(v_{xn})}{(exp(v_{xn}) + exp(v_{in}))^2}\frac{\partial v_{in}}{\partial R}\frac{\partial R}{\partial q} \\
&= t_n(1-t_n)\frac{\partial v_{in}}{\partial R}\frac{\partial R}{\partial q} \geq 0
\end{aligned} \tag{18}
$$

In other words, the share of *external* inventions should decrease with size. Note also that

$$
\begin{aligned}
&\frac{\partial^2 t_n}{\partial q \partial \delta} = (2t_n - 1)\frac{\partial v_{in}}{\partial R}\frac{\partial R}{\partial q}\frac{\partial t_n}{\partial \delta} + t_n(1-t_n)\frac{\partial v_{in}}{\partial R}\frac{\partial R}{\partial q}\frac{\partial R}{\partial \delta} \\
&t_n > \frac{1}{2} \implies \frac{\partial^2 t_n}{\partial q \partial \delta} \geq 0
\end{aligned} \tag{19}
$$

In other words, if the share of internal inventions among innovating firms is larger than half, size increases the use of internal inventions (or decreases the use of external), and has a differential effect on the use of internal inventions for firms of different capabilities.[8]

Proposition 6: The share of external inventions will decrease with size. Moreover, the share of external invention will decrease with size more quickly for high capability firms than low capability firms.

[8]We verify that empirically, the share of internal inventions is greater than half in the sample.

5 Data

We base our empirical analysis on the "division of innovative labor" (DoIL) survey of firms in U.S. manufacturing sector (Arora et al., 2016). Administered in 2010, the DOIL survey collected data on new product introductions at the level of the business unit within firms, for 2007 through 2009. The sample frame for this survey was the Dun and Bradstreet Selectory database, the most complete publicly available frame for the United States at the time.

The survey sampled all American manufacturing firms, not just R&D performers, unlike prior innovation-related surveys (e.g., Cohen et al. (2000); Levin et al. (1987)). Such a sample is key for the present exercise because it both allows construction of a measure of inventive capability that is not conditioned on endogenous innovation inputs (e.g., R&D) or outcomes (e.g., patents), and enables observation of the relationship between external supply of inventions and that of raw knowledge, respectively, and innovation for all types of firms.

Sampling was stratified along multiple dimensions, including industry (at the 4 digit NAICS level), and size (categories: Fortune 500, over 1000 employees but not F500, 500 to 1000 employees, 100 to 499 employees, and 10 to 99 employees, and less than 10 employees). For Fortune 500 firms, the sampling unit was the firm's activity within a NAICS; for other firms it was based on primary NAICS. The initial sample was 28,709. Initial screening (for out-of-business or out-of-population) left a final sample of 22,034. The final respondent count was 6,685 or an adjusted response rate of 30.3%. A more detailed description of the sampling process and complete description of the phone survey procedures, along with tables of response rates across industries, detailed tests of response bias, and other related information are outlined in Arora et al. (2016).

The survey asked responding firms about whether they had introduced a new product in the previous three years, and if so, whether the product was new to the market or merely new to the firm.[9] We describe firms that had introduced a product that was new to the market

[9] More precisely, of all the new products introduced, firms were asked to answer with respect to the most significant product, that which accounted for the largest share of revenues.

as innovators, and firms that introduced a product that was only new to the firm itself (i.e., not to the market) as imitators. Innovating firms were further asked whether they had acquired the key invention underlying their product innovation from an external source, such as a customer, a supplier, another firm in the industry, an independent inventor, an R&D contractor or university. To supplement the DoIL data, we matched each respondent to a location, and use the the relative incidence of R&D specialist firms in the region as a measure of the external supply of inventions, and proximate, relevant university R&D spending as a measure of the supply of external knowledge. Data sources for both are described below.

In the present study, we use businesses operating across all manufacturing industries (NAICS 31-33) with 10 or more employees, or 5,175 respondents. Because of item nonresponse on key variables (e.g., business unit size), our final sample for our latent class analysis is 4,692, out of which there are 1,124 innovators.

In all analyses we use survey sample weights, constructed using Census data on the population of firms stratified by industry, size strata, and age to correct for non-response bias.[10] We link the survey data outside datasets at the level of respondent (using Duns number or other firm identifiers), industry (NAICS 3 or 4 digit level), and location (county or metropolitan statistical area). Descriptions of the relevant additional datasets are listed below along with variable descriptions.

6 Latent class model

In this section, we provide a brief overview of the finite-mixture model approach we use to infer firms' inventive capabilities. Instead of using past behavior, e.g., patenting or R&D spending, to infer inventive capability, we use latent discrete choice models to generate a measure of capability. Latent class discrete choice models are a special case of finite-mixture models, which assume that the data generated are from a mixture of two (or more) distri-

[10]We constructed a matrix of these three dimensions of stratification (industry, size, and age) from a custom report provided by the U.S. Bureau of the Census. We thank Ron Jarmin and his team at the U.S. Bureau of the Census for providing this report.

butions, with different, unknown means. Each data point or observation has an unknown probability of belonging to one of the distributions (in latent class models, each distribution is a latent class). These (unknown) probabilities, along with the parameters of the distribution—that is, the set of coefficients from the model predicting innovation outcomes for each distribution—are jointly estimated.

Latent class models have been widely used in marketing to categorize consumers by their revealed preferences (Bordley, 1989; Boxall & Adamowicz, 2002; Bucklin & Gupta, 1992; Colombo & Morrison, 1989; Kamakura & Russell, 1989; Kamakura et al., 1996). These models allow for the attributes of various choices (e.g., price) and characteristics of the choosers (e.g., income) to differentially shape choices across endogenously determined preference groups or consumer types. For example, Kamakura et al. (1996) predict consumers choice of peanut butter, segmenting those insensitive to price (i.e., brand loyalists) from those who make choices based on price.

In our setting, we use latent class models to distinguish firm types by their underlying inventive capability, allowing business unit size and the external supply of inventions and knowledge to differentially shape innovation outcomes. As noted above, there are three potential innovation outcomes: (1) innovation, (2) imitation, or (3) no new product, here indexed by j. The probability of each outcome is: $P_i(j) = Prob(y_i = j)$, representing the class-specific estimates of the propensity to innovate, imitate, or do nothing or, in the multinomial logit formulation:

$$P_i(j) = \frac{e^{x_i \beta_j}}{\sum_{j=1}^{3} e^{x_i \beta_j}} \tag{20}$$

where x_i are the observed characteristics of firm i, and β_j are the coefficients associated with the j^{th} outcome.

If we allow these probabilities to vary across latent classes (hereafter q), the class conditional probabilities are $P_{i|q}(j) = Prob(y_i = j | class = q)$ or, in the multinomial logit formulation:

$$P_{i|q}(j) = \frac{e^{x_i \beta_{qj}}}{\sum_{j=1}^{3} e^{x_i \beta_{qj}}} \tag{21}$$

We do not directly observe membership in latent classes, and therefore it must be estimated. The estimation of class membership (i.e., probability of being in a class q) and the corresponding class-specific coefficients (β_{qj}) is an iterative process.

To estimate a latent class model, an analyst must first choose the number of classes q. To inform this choice, following prior literature (Greene & Hensher, 2003; Grimpe & Sofka, 2009; Roeder et al., 1999), we used the Akaike and Bayesian Information Criteria (AIC and BIC) as well as R^2 values. Table 3 highlights that the fit is greatly increased for our data in two classes versus one, and only increases slightly with 3 classes. Trading off interpretability (and thus fewer classes) against the additional fit from a higher number of classes, we choose two classes.

Latent class models simultaneously estimate class probabilities for each observation, class conditional probabilities of the various innovation outcomes, and class-specific coefficients. This means, for example, the effect of size on innovation outcomes is allowed to vary by class. Letting H_{iq} denote the prior probability of being in class q for firm i, z be a set of observable characteristics, and ϕ the corresponding coefficients. In our analysis, we use industry fixed effects in the estimation of initial latent class probabilities, i.e. as z.

$$H_{iq} = \frac{e^{z_i' \phi_q}}{\sum_{q=1}^{Q} e^{z_i' \phi_q}} \quad \text{where} \quad \boldsymbol{\phi_q} = 0 \tag{22}$$

The choice probability for respondent i is the sum of the class-level probabilities weighted by class probabilities, or: $P_i = \sum_{q=1}^{Q} H_{iq} P_{i|q}$.

After obtaining estimates of ϕ_q from the two class model, the latent class routine then computes choice probabilities and posterior estimates of the firm-specific class probabilities conditional on choice probabilities via Bayes theorem:

$$\hat{H}_{q|i} = \frac{\hat{P}_{i|q}\hat{H}_{iq}}{\sum_{q=1}^{Q}\hat{P}_{i|q}\hat{H}_{iq}} \tag{23}$$

These steps are repeated until the process converges. In the end, this analysis produces firm-specific estimates of latent class probabilities ($\hat{H}_{q|i}$), class-specific estimates of the propensity to innovate, imitate, or do nothing ($\hat{P}_{i|q}$), and class-specific coefficients for our predictor variables ($\hat{\beta}_{jq}$).[11] For comparison, as shown in Tables 1 and 4 discussed below, we also estimated the standard Multinomial logit (MNL) model that implicitly assumes there to be one latent class.

7 Analysis

Our analysis proceeds in two steps. Both follow from our theoretical predictions about innovation choices and sourcing by innovators. First, we analyze the likelihood of innovation, imitation, or not commercializing a new product. We use latent class discrete choice methods to simultaneously develop a measure of a firm's latent inventive capability and explore how inventive capability–along with measures of the external knowledge environment, business unit size, and other firm and industry characteristics–shape the choice to innovate, imitate, or not commercialize a new product. Second, we use our measure of latent inventive capability derived from our application of the finite mixture model approach subsequently examine if the patterns of association between firms' reliance on external invention, capability and firm size confirm the predictions of our model.

[11] The above steps were performed in NLOGIT 5 using LCLOGIT routines and in STATA 15 using the FMM module.

7.1 Analysis: Innovation, Imitation, and inventive capability

7.1.1 Outcome variable

We categorize business units as *innovators* if they earned revenue from a "new-to-the-market" product launched from 2007 to 2009. If the business unit earned revenue from a "new-to-the-firm" product launched over the same period that was not new-to-the-market, we categorized them as *imitators*. Those that did neither are categorized as *none*.

7.1.2 Discriminating variables

In our latent class regressions, we include a set of variables intended to discriminate between high and low capability firms. Our criteria for including regressors are notably different than in a typical regression with "explanatory" variables: we instead include regressors to help us to estimate and distinguish latent classes of firms. Building from our theory, we include a select set of variables that we expect will have differential relationships with our outcomes for high versus low capability firms.

Our theory emphasizes a distinction between two types of external inputs—external inventions and knowledge—which have different effects on innovation depending on firm inventive capability. We use the (log) count of R&D specialist firms in the MSA (Metropolitan Statistical Area) of the respondent business unit weighted by use of such services in the industry of the respondent as a measure of *external invention* supply. The measure therefore varies by region and industry.[12] [13]

[12] Specialist R&D suppliers consist of suppliers of Architectural, Engineering, and Related Services (5413), suppliers of Specialized Design Services (5414), Computer Systems Design and Related Services (5415), Management, Scientific, and Technical Consulting Services (5416), and Scientific Research and Development Services (5417). For our measure, we take a log of the count the number of large establishments (>100 employees) in NAICS 5413-5417 in the relevant MSA according the the US Census County Business Patterns data for 2007. For the industry weights, we use Bureau of Economic Analysis input-output tables to get the share of inputs coming from R&D specialists in each industry.

[13] Along with being sources of external inventions (Arora et al., 2001b) R&D specialists may also, however, diffuse knowledge inputs to internal invention. To examine the robustness of our results that employ this measure, we also ran our analyses using counts of relevant patents in the region of the respondent as defined by the Cluster mapping project (Delgado et al., 2014). The results using these cluster-based patents are qualitatively similar to our R&D specialist measure.

As our measure of external knowledge supply, we use proximate, relevant university R&D spending (within a 100 mile radius of the focal firm). To construct this measure, we used the NSF data on university R&D expenditures for 2004 through 2006. We count only R&D spending for research fields related to the industry of the respondent firm, and categorized relatedness based on whether R&D labs in the industry listed the field as relevant for research in a prior survey (Cohen et al., 2000).[14]

While we model external knowledge supply and external invention supply as separate parameters (k and s), they are difficult to separate empirically. Any measure of invention supply will also likely capture some element of knowledge supply. Further, even with separate measures of external invention supply and external knowledge supply for the local area of each respondent firm, areas rich in knowledge tend to be co-located with areas rich in inventions. Indeed, our two measures are strongly correlated (0.56). Given the collinearity between the two constructs, we conduct separate analyses below (Tables 1 and 4) to explore the potential differences in outcomes and behaviors associated with the external supply of knowledge as compared to those related to the external supply of invention.

Our theoretical analysis suggests that firm size, external knowledge supply and external invention supply should differentiate the innovative behavior of more capable from less capable firms. We measure *size* as the logged number of employees of the business unit. We also include several variables to control for differences across firms to isolate the theorized relationships. First, we include an indicator for whether or not the business unit is *multiproduct* (where *multiproduct* = 1 if the business unit has more than one associated 6-digit NAICS) since the scope of related firm activities has been found to be positively associated with invention and innovative success (Cockburn & Henderson, 2001; Henderson & Cockburn, 1996). We also include an indicator for whether the business unit is part of a larger firm or is a *standalone* company, and for *firm age*.

[14]In addition to providing a measure of externally available knowledge, proximate relevant university research activity may also, however, reflect inventions or capture the supply of trained personnel, an internal input into invention. Inventions resulting from university research constitute, however, only a very small share of the external inventions employed by firms.(Arora et al., 2016).

At the industry level, we include a dummy for whether or not the respondent is in a *high tech industry*, which is defined as whether the share of firms in the industry of the business unit that perform R&D is above the median (high tech = 1). On average, we expect firms in high tech industries to be more likely to innovate. We also control for whether or not the business unit is in a *homogeneous market*, that is, whether the market for the firm's innovation is relatively homogeneous (Sutton, 1998). Homogeneity is based on the share of total industry-level sales (4 digit NAICS) made up by the largest 7 digit NAICS category within the industry. We use total shipment values at the 4 and 7-digit NAICS level from the 2002 US Economic Census (homogeneous =1 for above median industries). Homogeneity should have competing effects on the choice between innovation and imitation.

7.2 Results: Innovation, Imitation, and inventive capability

Table 1 presents the results from simple multinomial logit (or single class) and latent class multinomial logit models (Appendix table A1 shows the posterior probabilities of being high capability across various industries). Table 2 includes the corresponding marginal effect estimates and average probability of each outcome for all three models. The best fit is provided by a model with two, rather than more or fewer latents classes. The fit statistics are outlined and described in Table 3.

We expect that one of the latent classes will be comprised of those with high inventive capability, and be characterized by higher innovation and imitation rates.That is, one class—which we label high capability—should be much more likely to have commercialized products via innovation and imitation than the other class of firms (Proposition 1). Further, the size of firms in the high capability class should have a larger, positive association with innovation and imitation as compared to that of low capability firms (Proposition 2). Finally, innovation and imitation by less capable firms should increase with external invention supply more than innovation and imitation by more capable firms (Proposition 3), and the reverse should be true for external knowledge (Proposition 4).

Across all firms, the average rate of innovation is 17%, of imitation is 25%, and 58% of firms did not commercialize a new product at all over the three year sample period, 2007 to 2009. As described above, each respondent is assigned a probability of belonging to each of the two latent classes.[15] For class 1, the predicted probability of innovation is 35%, of imitation 40%, and of no new product 24%. For latent class 2, the corresponding probabilities are 8% innovation, 16% imitation, and 76% none. Clearly, both innovation and imitation are, on average, much more likely for those that have a higher probability of being in latent class 1.[16] Henceforth, we refer to latent class 1 as "high capability", and use the likelihood that a respondent belongs to latent class 1 as a continuous measure of the inventive capability of the firm. Figure 1 highlights in more detail how the predicted probability of innovation, imitation and none changes as the firm's inventive capability increases. Consistent with Proposition 1, the share of innovation increase with capability, while the share imitation increases then declines with capability, per a similar discussion below regarding the relationship with size.

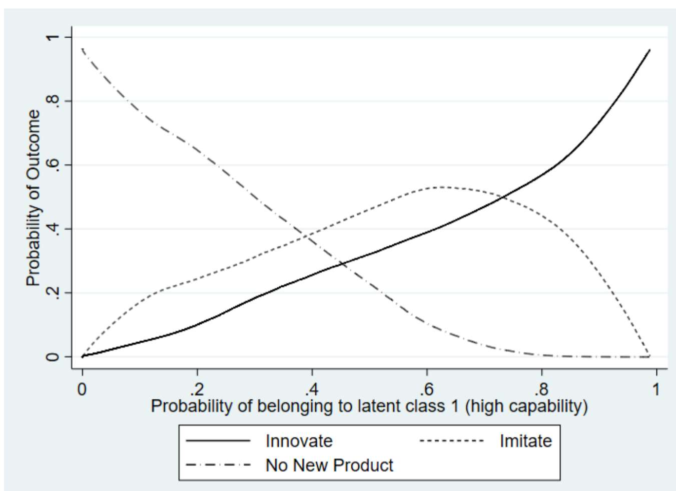


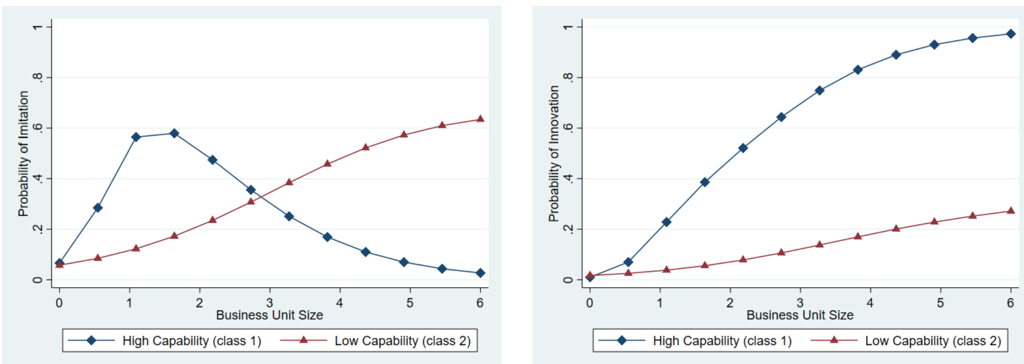
Figure 1: Likelihood of Innovation, Imitation and No New Product, by probability of belonging to latent class 1 (high capability)

Table 1 (Columns 4-9) shows that business unit size increases the payoff to innovation

[15] The average probability of an observation belonging to latent class 1 is 35%, and to latent class 2 is 65%.

[16] These outcome probabilities were generated using the full sample, using the probability associated with being in each class as weights. If, instead, we assign each respondent to a single class based on whether its probability of belonging to that class exceeds 0.5, we get: class 1 innovation is 45%, of imitation 53%, and of no new product 2%. For latent class 2, the breakdown is 4% innovation, 12% imitation, and 84% none.

and imitation for all firms. Figure 2, however, shows that the probability of imitation first increases and then decreases with size for high capability firms. For high capability firms, likelihood of imitation is the highest for mid-sized business units.[17] To better understand the size results (Figure 2), recall that firms have three options: innovate, imitate, or not commercialize new products. Loosely speaking, high capability firms choose between innovation and imitation. However low capability firms have much lower rates of substitution between innovation and imitation. Put differently, as firm size increases, the attractiveness of doing nothing falls for all firms. But for high capability firms, as size increases the relative attractiveness of innovation rises faster than imitation, because R increases with size, and the innovation payoff is more responsive to R than is the imitation payoff. Therefore the likelihood of innovating increases with size, whereas the likelihood of imitating is maximized at an intermediate size level. However, for low capability firms, the default outcome is not to do anything, and internal R&D is low. Thus, increases in size results in a monotonic increase in innovation and imitation.



(a) Imitation

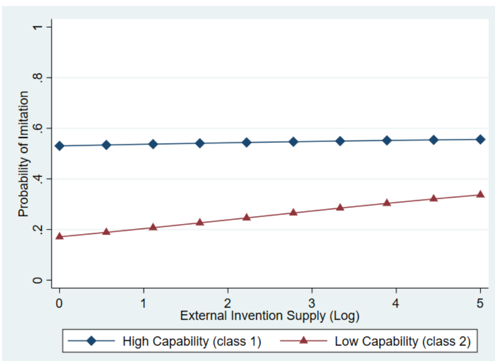
(b) Innovation

Figure 2: Likelihood of Innovation and Imitation, by Business Unit Size for High and Low Capability firms

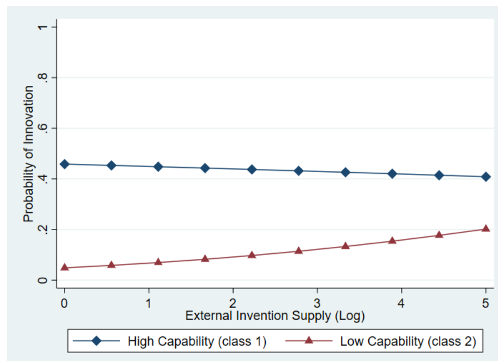
Propositions 3 and 4 from our theory suggest that the rates of innovation and imitation

[17]Other results are consistent with latent class 1 representing "high capability" firms (although such results are not part of our theory): (1) for latent class 1, being in a high tech industry is also positively associated with innovation, having a large effect (+20%), compared to latent class 2, where being in a high tech industry increases the probability of imitation by 5%; (2) for latent class 1, being in a more homogeneous market increases the likelihood of innovation by 11%, and of doing nothing by 20%, compared to latent class 2, where being in a more homogeneous market increases the likelihood of imitation by 13%.

of firms with more inventive capability will be: 1) less responsive to the external supply of inventions than firms with less inventive capability (Proposition 3); and 2) more responsive to a greater supply of external knowledge than firms with less inventive capability (Proposition 4). As shown in Table 1 consistent with Proposition 3, innovation and imitation by low capability firms (latent class 2) indeed appear more responsive to the supply of inventions than high capability firms. Figure 3 shows negligible difference in the probability of innovation or imitation across the range of external invention supply for high capability firms, and an increase of approximately 10% in imitation and 15% in innovation across the range of invention supply for low capability firms.



(a) Imitation



(b) Innovation

Figure 3: Likelihood of Innovation and Imitation, by External Supply of Invention (R&D specialists) for High and Low Capability firms

In Table 4, to investigate Proposition 4 (the relationship between external knowledge supply, capability, and innovation/imitation/none), we duplicate our analysis from Table 1, but look at external knowledge supply (measured using university R&D spending) instead of invention supply. Here, we see that high inventive capability firms innovate more in the presence of external knowledge supply, while low capability firms do not innovate more but do imitate at higher rates.[18] The former point reflects our arguments that high capability firms mainly extract raw knowledge inputs from the outside. Although our model also predicts

[18]The increased likelihood of imitation by low capability firms when they are exposed to greater knowledge supply is predicted by our model. Taken together with the findings on innovation, one possible explanation for the increases in imitation by low capability firms is that more knowledge, by allowing for greater innovation rates by more capable firms, may also yield more innovations for low capability firms to imitate.

that innovation should increase with external knowledge supply for low capability firms, we do not find this to be the case.

The divergent results between inventive capability and the external supply of, respectively, inventions and knowledge highlight a key point of our paper: firms of high and low inventive capability capitalize upon the different forms of knowledge that are available externally. Low capability firms seek external inventions—their main source of invention and, in turn, innovation. Thus, for low capability capability firms, external inventions are a substitute for internal inventive efforts. However, the internal inventive efforts of high capability firms benefit from their external environment via more upstream knowledge inputs (i.e., ideas, findings, etc.). To put it starkly, low capability firms are less capable of introducing new products without the help of external inventors, but high capability firms can. Moreover, high capability firms are more likely than low capability firms to use raw knowledge from their external environment.

Given that Tables 1 and 4 generate, for each observation, a measure of the probability that that a firm belongs to the high capability class, this raises the question whether the two generated sets of measures reflect the same underlying construct. To address the question, we correlate the two sets of estimates. As Table 5 shows, both result in very similar assignments of firms to high and low capability classes, with a correlation of 0.89.

7.3 Inventive Capability and External Sourcing

Given our findings on inventive capability in Tables 1 and 4, we turn to examining how the use of external inventions differs across firms of varying capability and size. From Propositions 5 and 6 above, we expect the conditional (on innovation) probability of using external inventions among innovators to be lower for both high capability firms and larger firms. We approach this question non-parametrically since a more complete model of the determinants of the use of external inventions is beyond the scope of this paper. Accordingly, we run a simple cross tab on our sample of innovating firms, where firms are distinguished by size (large and small) and inventive capability (high and low). For our measure of *inventive capability*, we use our estimate of the probability that the firm has high inventive capability, estimated via the latent class regression in Table 1, and split firms into high and low capability on the basis of the median value. To distinguish small from large business units, we split at 500 employees.

We construct our measure of whether innovating firms acquire the underlying inventions externally or generate them internally from responses to the DoIL survey (Arora et al., 2016), discussed above. We identify the source of the invention to be external if the respondent said one or more of the following was the main source of the overall concept, prototype or design underlying its innovation (i.e., new product): a supplier; a customer; another firm in the industry; a consultant, commercial lab, or engineering service provider; an independent inventor; or a university or government lab. The alternative was that the innovation was based on an internal invention.

The results from our cross tab are presented in Table 6. Proposition 5 above suggests that less capable firms should be less likely to rely more on external inventions, and Proposition 6 suggests that larger firms should be less likely to rely upon an external inventions. The results presented in Table 6 accord with both predictions, with the percentage of smaller firms acquiring their inventions from an outside source exceeding that of larger firms by about four percent, and the percentage of less capable firms doing so exceeding that of more capable firms by just over a percent. Moreover we see a greater drop associated with greater capability among larger firms, where the drop is almost six percent. If we compare small, less capable firms with larger, more capable firms, the former's reliance upon external invention, 49.3%, exceeds that of the latter by nine percentage points, representing a difference of almost one quarter of the 40.3% of larger, more capable firms' that rely upon external inventions. These results add nuance to our discussion of the Table 1 and 4 results above. First, more capable, larger firms acquire inventions; they do not rely exclusively upon external knowledge for their new products. The results are also consistent, however, with one of our main points: that whereas small, low capability firms innovate mainly by commercializing inventions made by others, large, high capability firms rely mainly upon internal inventions for their new products.

In our original characterization of “inventive capability” above, we suggested that this capability was largely technical. What this would suggest is that firms with less inventive capability would be more likely to access inventions with less technical content. To probe this conjecture, we take advantage of the DoIL data that distinguishes externally acquired inventions by source. We conjecture that inventions originating from customers will have less technical content on average as compared to inventions originating from universities, R&D service contractors, and startups. As a consequence, the acquisition of inventions from customers should require less technical inventive capability as compared to acquisitions from other external sources. Exploring this conjecture, Table 7 presents the results of a multinomial logit where the reference category is internal invention and column (1) presents the predicted likelihood of using an invention from a non-customer source versus an internal invention, and column (2) presents the predicted likelihood of using a customer-sourced invention relative to internal invention. Confirming our prior, the results in column (2) show that, as inventive capability increases, innovating firms are less likely to rely upon a customer-sourced invention as compared to internal invention. In addition to providing suggestive evidence that our capability measure reflects a technical capability, this result also highlights the broader point that external inventions may differ from one another in systematic ways, and that those differences have implications the role of inventive capability in affecting their acquisition. A second result in Table 7 should, however, give us pause. The coefficient on inventive capability in column (1) is essentially zero. In other words, high capability firms derive the same payoff from non-customer sources of inventions as internally generated inventions. This result is inconsistent with our theory. But, in our view, what it highlights is the starkness of our model: To the degree that external inventions have greater technical content, internal inventive capability may play a role not only in internal invention, but also in the acquisition of more technical inventions.

7.3.1 Validating our Capability Measure

We are interpreting the above results on the premise that the capability that we are measuring using our finite mixture empirical model is indeed inventive capability rather than, for example, the more downstream capability to commercialize new products. Indeed, our findings that more capable firms are more likely to exploit external knowledge and not use external inventions, while less capable firms are more likely to exploit external inventions, is certainly consistent with this interpretation. Nonetheless, we performed additional analyses to both confirm our view of what we are measuring and investigate the robustness of our capability measure.

First, we examined the association between our measure of inventive capability and two key measures of inventive activity, namely R&D investment and past patenting (for the period 2002 to 2006). Controlling for industry, high capability firms are 38% more likely to have performed R&D (54% versus 15%) and almost twice as likely to have filed for a patent (9% versus 5%) over a three year period.

For another source of confirmation that we are measuring inventive capability, we also examined the association between our measure and a measure drawn from the DoIL survey where respondents reported not only whether they commercialized a new product, but also developed or licensed out a technology to another firm. We suggest that such a practice would more commonly apply to firms that possess inventive capability, and thus have internal inventions available for sale or licensing. And, indeed, we find, controlling for industry, high capability firms are two and a half times more likely to have been a technology supplier (23% versus 9%) in the past three years.

Collectively, these associations provide additional support for our interpretation of our latent variable measure as reflecting “inventive capability.”

8 Inventive Capability and Performance

In this section, we explore the relationship between inventive capability and business unit performance. Obviously the question of the determinants of firm performance is a big one. Here our ambitions are modest—to simply consider whether the patterns of association between our measure of inventive capability and performance are consistent with our conception of the role and impact of inventive capability as presented in our model.

Drawn from the DoIL survey (Arora et al., 2016), our measure of business unit performance is whether a business unit experienced market share growth between 2008 and 2009, the end of our sample period. Our sample for this analysis is the full set of survey respondents regardless of outcome, and our measure of inventive capability here is continuous, i.e. the likelihood of being high capability. It is important to remember that, having constructed our measure of inventive capability from the latent class model, firms with high inventive capability do not necessarily innovate; they may imitate or even do nothing.

Table 8 reports the results of a linear probability model on the likelihood of market share growth. The column (1) result shows a positive significant relationship between inventive capability and market share increase, as expected. Per our model, inventive capability affects performance through the payoff from innovating or from imitating (using internal sources), and therefore, also on whether the firm innovates or imitates (as opposed to not introducing any new product to the market place). In column (2), along with inventive capability, we thus include our outcome measures, innovate and imitate. Given that our model would suggest that inventive capability should benefit the firms' performance through one of these two outcomes, one would expect the relationship between inventive capability and market share to weaken. Instead, the outcomes should be directly related to performance. Indeed, this is exactly what we see in column (2).[19]

[19]Our model can be applied more formally to guide our expectations about performance. Let $Y =$ performance such that: $Y = E(V_j + \epsilon_j | \text{j is chosen}), j \in \{innovate, imitate, none\}$. Then, the simple effect of capability on Y is approximately $\frac{\partial V_{in}}{\partial \delta} t_n \psi_n + \frac{\partial V_{im}}{\partial \delta} t_m \psi_m > 0$, where t_n is the share of innovations based on internal inventions and ψ_n is the share of innovating firms, and t_m and ψ_m are defined analogously. Also, note that $\frac{\partial V_{in}}{\partial \delta} = \frac{\partial V_{in}}{\partial R} \frac{\partial R}{\partial \delta} > \frac{\partial V_{im}}{\partial \delta} > 0$. In short, the main effect of capability on performance (conditional

In our model, inventive capability increases R&D effort and the relative impact of R&D is greater for the payoff from innovation than for imitation. Thus, if the firm actually innovates, one would expect capability to have a bigger impact on performance than if the firm imitates. To test this, column (3) in table 8 includes interactions between inventive capability and the two outcomes of imitate and innovate. The results are again consistent with our theory, suggesting that if firms have applied their inventive capability to innovating rather than imitating, the likelihood of increasing their market share should increase, which we observe by comparing the interactions of capability with innovation and imitation.

As a side note, it is also interesting to see that business unit size is associated with an increase in market share in column (1), but once we control for whether the firm has innovated or imitated, the effect of business unit size dissipates, which is consistent with the notion that the impact of business unit size on market share works through its effect on decisions to innovate and imitate.

9 Discussion and Conclusions

Using a model of firms' decisions to innovate and data for the U.S. manufacturing sector, we explore the relationships that link firms' innovative activities, their inventive capabilities, and the supply of external knowledge. We develop a simple theoretical model of the relationship between a firm's inventive capability and the three innovation outcomes (innovate, imitate, or neither), and how that relationship is conditioned by the supply of the two forms of external knowledge as well as firm size. Guided by the theory, we employ a finite-mixture model that

on choice of outcome) should be positive. Our model also has implications for the relationship between capability and performance across different outcomes. Intuitively, the coefficient of the interaction between capability and innovation represents $\frac{\partial V_{in}}{\partial \delta} t_n$, and analogously, the coefficient of the interaction between capability and imitation represents $\frac{\partial V_{im}}{\partial \delta} t_m$. We would expect both are positive. In terms of relative size, since innovation is more responsive to R&D and hence to capability than is imitation, provided the share of imitation from internal R&D is smaller than the share of innovation based on internal R&D, or at least, the difference in shares is not large enough to outweigh the differential responsiveness to R&D, we would expect the interaction between capability and imitation to be much smaller than that between capability and innovation.

simultaneously assigns firms to an "inventive capability" class (i.e., high or low), and estimates how the relationship between the supply of external knowledge (i.e., either "raw" knowledge or inventions) and firms' innovative activities is conditioned by that capability. We then explore how firms' use of external inventions is conditioned by their inventive capabilities and size. In our final step, we examine the relationship between inventive capabilities and firms' market performance, measured in terms of increases in market share.

Perhaps the most striking finding from our analysis is that increasing the external supply of inventions contributes more to the innovative activity of less capable firms, and less to that of the more capable. In this sense, a greater supply of invention helps less capable firms compete. The innovative activity of more capable firms does increase with greater knowledge flows, while such knowledge flows have little association with the innovations of less capable firms. Thus, we document two effects: more innovation on the part of less capable (versus more capable) firms when exposed to more external inventions, and more innovation on the part of more capable firms when exposed to a greater supply of knowledge. Our argument is essentially that external inventions can substitute—and thus compensate—for the inability of firms to invent. In contrast, external knowledge complements inventive capability, enabling greater innovation on the part of more capable firms. Concretely, increasing the supply of external invention, for instance by thickening technology markets, strengthens the ability of less capable firms to innovate, and, thus compete. At the same time, however, more capable firms are able to capitalize on greater external supply of raw knowledge—such as that which may originate from universities or R&D spillovers from rivals—to innovate more. We also try to address the question of why and how inventive capability may matter for firm performance. Our measure of performance, market share, is of course limited, and our analysis is strictly correlational. Nonetheless, our findings are consistent with the notion that inventive capability matters, and that, while it works through its effect on both innovation and imitation, it matters more when the channel is innovation.

To come to these conclusions, we have bridged several literatures that focus on the division of innovative labor, each of which emphasize only one form of external knowledge. The literature on R&D spillovers, geography and absorptive capacity focuses largely on raw knowledge, while the literature on markets for technology tends to focus only on the movement of inventions across organizations. As noted above, our finding that local knowledge flows have a positive relationship with innovation is consistent with prior findings on the geography of innovation, which typically argues that agglomeration allows firms to access to knowledge spillovers that help firms to generate inventions. Our findings, however, suggest that high capability firms are more likely to use knowledge spillovers to innovate. In contrast, to the extent that less capable firms benefit from a propitious location, our findings suggest that the result is not due as much to the flow of knowledge as to the external inventions that other firms generate.

In addition to our substantive findings, our study contributes methodologically to the study of firm capabilities. We generate a measure of latent inventive capability that correlates with, but is not determined by, prior invention inputs like R&D, or prior invention outcomes like patenting. Latent measures of inventive capability provide a way to measure capabilities in industries where patenting is uncommon, and for firms for whom R&D data may not be systematically available, such as private firms. Our measure also does not involve detailed measurement of distance to the cutting edge of the technological trajectory within an industry (as in e.g., Franco et al. (2009)) and is therefore measurable and potentially applicable for cross-industry studies. Finally, firms can have high inventive capability and not innovate, or have low inventive capability and innovate. A potential extension of this method would be to use new product introductions, perhaps measured using trademarks, alongside firm, industry, and other characteristic variables to similarly estimate commercialization capability, and explore the development and influence of both inventive capability and commercialization capability over time.

Our study also offers several practical implications. For managers seeking growth, an important question is whether or not to invest substantial resources in R&D expenditure or to pursue a different strategy. Our findings suggest this will depend on both their existing capabilities and the availability of inventions and knowledge. Specifically, for high capability firms, investing in R&D will help them to invent and enable access to external knowledge inputs. However, while we do not address it in our paper, high capability firms in rich environments are also at a greater risk of being imitated (Alcácer & Chung, 2007; Giarratana & Mariani, 2014). In contrast, investing in R&D may not help low capability firms for whom innovation is more about sourcing external invention. Instead, investing in complementary commercialization resources may be more advisable if external inventions are plentiful. Moreover, an obvious implication for less capable firms is to locate either in markets or geographies with strong supply of inventions.

Our conclusions require a number of qualifications. We only take one step in probing the relationship between firm capabilities and the division of innovative labor. Due largely to data limitations, we study the role of inventive capability in innovation, not firms' commercialization capabilities such as manufacturing, marketing and sales. Our data are survey based, and therefore are subject to the caveats associated with such data. The cross-sectional nature of our data prevent us from exploring dynamic relationships between capability, innovation, and performance. Finally, we have to assume that the supply of knowledge and inventions is exogenous. Concretely, this would imply, for example, that firm location in a rich or poor external knowledge environment is exogenous. Instead, firms may choose their location in part to access external inventions or knowledge.

Our theory is stark in its assumptions, including, for example, that inventive capability does not affect the payoffs from using external inventions. Our results in Tables 6 and 7 suggest the reality is more complex. We suggest, however, that distinguishing between inventive capability and commercialization, and between knowledge and invention as inputs into innovation, enables us to clarify the confusion and seeming contradiction between literatures on their view of whether external knowledge complements or substitutes for the firm's own capabilities. While we make an important methodological contribution by measuring a particular type of capability at a point in time, capabilities are clearly cumulative, shaped by prior experience and learning. We hope future research continues to develop measures of latent capability.

Table 1: Innovation, Imitation or None: Multinomial and Latent Class Logits

	MNL			Latent Class Logit: 2 classes					
				Latent class 1			Latent class 2		
	inno vs none (1)	imi vs none (2)	inno vs imi (3)	inno vs none (4)	imi vs none (5)	inno vs imi (6)	inno vs none (7)	imi vs none (8)	inno vs imi (9)
Standalone	0.09	0.16	-0.07	-2.37	-3.43*	1.06	-0.71	0.97*	-1.69*
	(0.15)	(0.14)	(0.16)	(1.99)	(1.90)	(0.88)	(0.46)	(0.56)	(0.88)
Multiproduct BU	0.21**	-0.06	0.27**	-0.25	-0.29	0.04	0.71**	-0.07	0.78*
	(0.10)	(0.08)	(0.11)	(0.43)	(0.39)	(0.32)	(0.34)	(0.22)	(0.43)
BU size (log)	1.01***	0.66***	0.35***	4.25***	3.29***	0.96***	0.80***	0.80***	-0.01
	(0.07)	(0.07)	(0.07)	(0.89)	(0.78)	(0.34)	(0.22)	(0.13)	(0.27)
Firm age (years)	-0.004*	-0.003*	-0.001	-0.05***	-0.02***	-0.02***	0.02**	-0.01	0.02***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
High tech industry	1.00***	0.31***	0.70***	1.93***	0.81	1.12***	0.41	0.39	0.02
	(0.10)	(0.09)	(0.11)	(0.50)	(0.53)	(0.35)	(0.35)	(0.25)	(0.48)
Homogeneous industry	0.06	-0.01	0.07	-1.01*	-2.31***	1.30***	-0.77	1.01***	-1.79***
	(0.10)	(0.09)	(0.11)	(0.54)	(0.79)	(0.49)	(0.50)	(0.32)	(0.64)
External Invention Supply	0.13***	0.11***	0.02	-0.23	-0.24	0.01	0.37**	0.24**	0.13
	(0.05)	(0.04)	(0.05)	(0.21)	(0.24)	(0.14)	(0.17)	(0.11)	(0.20)
Constant	-3.37***	-2.04***	-1.33***	-1.4	1.37	-2.77**	-4.29***	-4.15***	-0.14
	(0.24)	(0.21)	(0.25)	(2.05)	(1.74)	(1.22)	(1.17)	(0.81)	(1.59)
Avg class prob					0.35			0.65	
Observations		4692				4692			
ll		-3671.69				-3616.66			

Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1

These regressions predict the likelihood of a firm innovating, imitating, not commercializing a new product, using a multinomial logit (columns 1-3) and latent class logit (columns 4-9) specification. Regressors include: external invention supply, whether a firm is standalone (versus part of a multiunit firm), whether the firm operates in multiple submarkets within their industry (multiproduct BU), firm size and age, and whether the firm is in a high tech industry and a homogeneous industry. Coefficients represent the change in log odds: marginal effects are listed in Table 2.

Table 2: Innovation, Imitation or None: Average Marginal Effects

	MNL			Latent Class Logit: 2 classes					
				Latent class 1			Latent class 2		
	Pr(none) (1)	Pr(imi) (2)	Pr(inno) (3)	Pr(none) (4)	Pr(imi) (5)	Pr(inno) (6)	Pr(none) (7)	Pr(imi) (8)	Pr(inno) (9)
Standalone*	-0.03	0.03	0.00	0.34	-0.36	0.02	-0.07	0.12	-0.05
Multiproduct BU*	-0.01	-0.02	0.03	0.03	-0.02	-0.01	-0.03	-0.01	0.04
High tech industry*	-0.13	0.02	0.10	-0.14	-0.06	0.20	-0.07	0.05	0.02
Homogeneous industry*	0.00	-0.01	0.01	0.20	-0.31	0.11	-0.08	0.13	-0.05
External Invention Supply	-0.03	0.02	0.01	0.03	-0.01	-0.01	-0.05	0.03	0.02
BU size (log)	-0.18	0.08	0.09	-0.40	0.13	0.27	-0.13	0.09	0.04
Firm age (years)	0.001	-0.001	0.00	0.003	0.001	-0.004	0.00	-0.001	0.001

* Indicator variables

Marginal effects represent the increase in probability of an outcome (as compared to any other alternative). For indicator (0/1) variables, it is the increase in probability associate with a change from 0 to 1 (e.g., average increase in probability from being a standalone firm).

Table 3: Tests for fit: number of latent classes

Classes	LL	R2 (McF)	AIC	BIC	N	K
4	-3578.9	0.197	7291.8	7724.1	4692	67
3	-3599.0	0.192	7298.0	7620.7	4692	50
2	-3630.3	0.185	7326.5	7539.5	4692	33
1	-3671.7	0.058	7375.4	7478.6	4692	16

This table present the fit statistics across the one, two, three, and four class models which we used to select the number of latent classes. The McFadden R^2 and log likelihood values suggest models with more than one class provide much better fit (i.e., in one class model is 0.06 and is more than 0.18 in the two, three or four class models). Yet, the AIC and BIC are lower in the single class model. Balancing these diagnostics, and aiming for interpretability, we chose a model with two latent classes.
Note: BIC=2*LL+K*ln(N)

Table 4: Innovation, Imitation or None: Multinomial and Latent Class Logits, External Supply measured by University R&D (knowledge)

	MNL			Latent Class Logit: 2 classes					
				Latent class 1			Latent class 2		
	inno vs none	imi vs none	inno vs imi	inno vs none	imi vs none	inno vs imi	inno vs none	imi vs none	inno vs imi
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Standalone	0.09	0.16	-0.07	-5.01	-3.59	-1.42	0.77*	-0.18	0.95
	(0.15)	(0.14)	(0.16)	(4.03)	(3.71)	(1.07)	(0.46)	(0.35)	(0.69)
Multiproduct BU	0.22**	-0.06	0.27**	1.27*	-0.14	1.40*	-0.12	0.23	-0.35
	(0.10)	(0.08)	(0.11)	(0.68)	(0.41)	(0.75)	(0.22)	(0.25)	(0.36)
BU size (log)	1.01***	0.65***	0.35***	4.11***	2.87***	1.24**	0.74***	0.71***	0.03
	(0.07)	(0.07)	(0.07)	(1.12)	(0.78)	(0.56)	(0.15)	(0.16)	(0.24)
Firm age (years)	-0.003**	-0.003*	0.00	-0.01	-0.03***	0.01	-0.01*	0.01	-0.01**
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)
High tech industry	1.04***	0.34***	0.70***	0.35	0.34	0.02	1.38***	0.05	1.33***
	(0.10)	(0.09)	(0.11)	(0.62)	(0.44)	(0.63)	(0.22)	(0.34)	(0.46)
Homogeneous industry	0.05	-0.02	0.07	-2.56**	-0.45	-2.11**	0.68**	-0.50	1.18*
	(0.10)	(0.09)	(0.11)	(1.02)	(0.45)	(1.06)	(0.28)	(0.47)	(0.61)
External knowledge supply	0.02*	0.01	0.01	0.17*	-0.03	0.20*	-0.01	0.12***	-0.13**
	(0.01)	(0.01)	(0.01)	(0.09)	(0.05)	(0.11)	(0.02)	(0.04)	(0.05)
Constant	-3.50***	-2.09***	-1.41***	-2.69	1.84	-4.53**	-3.78***	-4.21***	0.43
	(0.26)	(0.23)	(0.28)	(3.38)	(3.71)	(1.83)	(0.60)	(0.92)	(1.11)
Avg class prob					0.30			0.70	
Observations		4692					4692		
ll		-3674.6					-3622.56		

Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1
These regressions predict the likelihood of a firm innovating, imitating, not commercializing a new product, using a multinomial logit (columns 1-3) and latent class logit (columns 4-9) specification. Regressors include: external knowledge supply, whether a firm is standalone (versus part of a multi-unit firm), whether the firm operates in multiple submarkets within their industry (multi-product BU), firm size and age, and whether the firm is in a high tech industry and a homogeneous industry. Coefficients represent the change in log odds.

Table 5: Relationship between latent class assignment: Invention Supply (Table 1) versus Knowledge Supply (Table 4)

		Table 4	
		Low Capability	High Capability
Table 1	Low Capability	2865	282
	High Capability	116	1711

This table presents a cross tabulation of the latent classes (capabilities) from Table 1 which uses R&D specialists to measure external invention supply and Table 4 which uses university R&D to measure external knowledge supply. The off-diagonal values represent the number of firms differentially classified across the two analyses.

Table 6: The share of innovators using external sources, by inventive capability and BU size

	Small BU	Large BU	All sizes
Low Capability	0.493	0.457	0.487
	(0.040)	(0.049)	(0.034)
High Capability	0.479	0.403	0.475
	(0.029)	(0.065)	(0.028)
All capability	0.485	0.444	0.480
	(0.023)	(0.039)	(0.020)

This table presents a cross tabulation of the use of external sources by innovating firms across both inventive capability and business unit (BU) size. Standard errors in parentheses.

Table 7: Sources of invention: internal, customers, other external source, among innovating firms Ref cat: Internal source

	non-cust (1)	cust (2)
Inventive capability	0.11	-0.53*
	(0.28)	(0.28)
BU size (log)	-0.04	-0.27**
	(0.12)	(0.12)
Ext invention supply	0.32	-0.35
	(0.25)	(0.22)
Vertically integrated	0.56**	0.52**
	(0.24)	(0.24)
Multiproduct BU	-0.32	-0.43*
	(0.24)	(0.24)
Industry FE	Yes(17)	Yes(17)
Constant	-0.69	-0.21
	(0.49)	(0.55)
Observations	1,124	
LL	-660.8	

Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1

These regressions predict the likelihood of an innovator firm using non-customer or customer sourced invention, as compared to internal (the reference category). The predictors are: firm inventive capability, firm size, external invention supply, whether is vertically integrated (i.e., has supplier or customers inside the same firm), whether the firm operates in multiple submarkets within their industry (multiproduct BU), and 17 industry fixed effects.

Table 8: Market share increase, by innovation outcome and capability (linear probability)

	Market Share Increase		
	(1)	(2)	(3)
Inventive capability	0.20***	-0.00	-0.11
	(0.03)	(0.06)	(0.11)
Innovate		0.18***	0.02
		(0.05)	(0.07)
Imitate		0.13***	0.17***
		(0.03)	(0.06)
Capability * Innovate			0.32**
			(0.13)
Capability * Imitate			0.01
			(0.15)
BU size (log)	0.03**	-0.00	-0.01
	(0.01)	(0.01)	(0.02)
Start-up BU	0.20***	0.20***	0.19***
	(0.06)	(0.05)	(0.06)
Constant	0.53***	0.58***	0.60***
	(0.04)	(0.04)	(0.05)
Industry FE	Yes(45)	Yes(45)	Yes(45)
Observations	4,316	4,316	4,316
R-squared	0.04	0.05	0.05
LL	-3036	-3021	-3016

Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1

These regressions predict the likelihood the focal respondent business unit experienced a market share increase from 2008 to 2009. The predictors are: firm inventive capability, firm size, external invention supply, whether is vertically integrated (i.e., has supplier or customers inside the same firm), whether the firm operates in multiple submarkets within their industry (multiproduct BU), and 45 industry fixed effects.

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Appendix

Table A1: Latent Class Probabilities

	class 1 (vs class 2)
Food & Textiles (NAICS 31)	-0.695**
	(0.260)
Wood & Chemicals (NAICS 32)	-0.571**
	(0.257)
Pharmaceuticals (NAICS 3254)	0.294
	(0.332)
Machinery & Transport (NAICS 331-3, 37)	-0.360*
	(0.218)
Computers/Electronics (NAICS 334)	1.639***
	(0.515)
Semiconductor (NAICS 3344)	0.611*
	(0.318)
Instruments (NAICS 3345)	0.582
	(0.455)
Electrical Equipment (NAICS 335)	-0.106
	(0.258)
Transportation (NAICS 336)	0.055
	(0.316)
Medical Equipment (NAICS 3391)	0.683
	(0.427)
Constant (Ref: Misc Manu (NAICS 339))	0.241
	(0.457)

Robust standard errors in parentheses. ***$p<0.01$, **$p<0.05$, *$p<0.1$