

From Invention to Innovation: Conversion Ability in Product Development

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Abstract

The ability to convert inputs into outputs is a critical determinant of success in many fields of endeavor. In this research we study the ability of firms to convert ideas into products, i.e., their conversion ability. Specifically we address the question: *Why are some firms better at conversion than others?*

As a response to pressures to innovate, many firms have gravitated toward generating larger numbers of promising ideas, and increasing the speed with which these ideas are taken to the market. Relatedly, the product development literature has frequently highlighted the virtues of increased speed and increased idea generation. In contrast, we propose that a strong focus on speed and on generating many ideas may actually **hurt** firms, by lowering their conversion ability.

We present a number of hypotheses on why some firms are better at conversion than others, and test these on data between 1960 and 2001 from a cross-national sample of pharmaceutical firms. We find that converting promising ideas to launched drugs is no easy task: only about 20% of patented drug ideas make it to product launch. We also find that firms vary widely in their ability to convert promising drug ideas to launched drugs. Firms with the highest conversion ability are those that: 1) focus on a moderate number of ideas, in areas of importance, and in areas where they have expertise, and 2) deliberate for a moderate length of time on promising ideas.

From Invention to Innovation: Conversion Ability in Product Development

The quest to convert inventions (promising ideas for products) to innovations (commercialized products) is a central feature of technological progress and economic growth. Firms, whether working out of tiny garages or in sprawling research labs, sink much hard-won capital to generate inventions and bring them speedily to market. Every stage of product development adds substantially (and cumulatively) to costs. These costs have large implications for firms, policy makers, and consumers.

For example, DiMasi, Hansen, and Grabowski (2003) estimate the average R&D cost for a new chemical entity launched in the US pharmaceutical market to be \$802 million. Estimates such as these (also see DiMasi 2001; Hansen 1979) are frequently used in policy debates and decisions (see US Congress, Office of Technology Assessment 1993; US Congress, Congressional Budget Office 1994). Part of the reason these estimates are so large and controversial is that they take into account the cost of ideas that failed to make it to launch (Danzon, Nicholson, and Pereira 2003). The odds of a promising idea making it past the various stages of drug development to eventual product launch are, on average, less than one in five.

However, the odds can vary substantially across firms. If so, then estimates of development costs per launched product will also vary substantially across firms (see Stevens and Burley 1997). Efficiency in product development due to higher conversion rates can yield resource savings that can be reallocated in other ways, such as in lower prices, higher profits, or greater investment in future innovation. And yet, differences in conversion rates are rarely discussed in policy debates. The implicit assumption appears to be that firms have little control over conversion rates, and all firms are subject to the same odds of conversion. The drivers of conversion ability remain a mystery, and research on the issue is rare.

This paper studies conversion ability in the pharmaceutical industry. **Conversion ability** is a firm's ability to translate a given idea into a launched product. As such, a firm is deemed to have high conversion ability if its likelihood of converting a given idea to a launched product is higher than that of other firms. We show that firms vary dramatically in their conversion ability, and address the question: *Why are some firms better at conversion than others?*

Part of the difficulty in answering questions about conversion is data availability—on inputs (i.e.,

promising ideas) as well as outputs (i.e., launched products). Greenley and Bayus (1994) review the literature on product launch, and note that despite an extensive search, they were unable to find any empirical studies on why some products make it to launch and others do not (also see Scott Morton 1999; Tholke, Hultink, and Robben 2001). The problem of data availability is even worse at the input stage. Empirical research on conversion requires data on the number of promising ideas in a firm. This data is exceedingly difficult to quantify. Ideas are dispersed across many individuals and many areas within firms. Moreover, firms have highly varying propensities to record and report information on development projects. Failures are quickly forgotten, and are hard to track. Many firms, for secrecy and policy reasons, keep projects in development strictly under wraps, or deep inside a file drawer, as the case may be. For all these reasons, it is extraordinarily difficult to obtain comparable data across firms. Although researchers have noted the importance of conversion ability in contexts ranging from academia (Taylor et al. 1984) to advertising copy selection (Gross 1972) to chemicals (Stevens and Burley 1997), large-scale empirical research on conversion is well-nigh impossible in most contexts.

The pharmaceutical industry is an important exception. The researcher has access to reliable data on both ends of the conversion process in this industry. On the output side, pharmaceutical regulatory bodies provide detailed data on all drugs that have been approved for launch within their areas of jurisdiction. On the input side, some institutional characteristics of the pharmaceutical industry facilitate the collection of accurate, comprehensive, and comparable data on the promising ideas in individual firms (Arundel and Kabla 1998; Cohen, Nelson, and Walsh 2000).

Moreover, product development is the lifeblood of the pharmaceutical industry. New drugs have dramatically impacted the lives of many patients (Gambardella 1995) and the bank accounts of many shareholders (Sorescu, Chandy, and Prabhu 2003). Nevertheless, as we noted earlier, drug development is an extraordinarily expensive proposition, and converting promising ideas to launched drugs is no easy task.

Given strong pressures to innovate and bring forth a steady stream of launched products, many managers have gravitated toward two popular solutions: 1) generate larger numbers of promising ideas, and 2) increase the speed with which ideas are brought to market. Indeed, these pressures have spawned a vast

literature in new product development on methods to increase idea generation (Sowrey 1987, 1990; Verhage, Waalewijn, and van Weele 1981). An implicit assumption in the idea generation literature is that generating a greater number of ideas leads to greater innovation outputs.

A large literature has also dealt with the advantages of bringing a product to market fast (Choperena 1996; Griffin 1997; Kessler and Chakrabarti 1996). In the context of the pharmaceutical industry, for example, Getz and de Bruin (2000, p. 78) note that “by shortening development cycle time, companies can both extend patent-protected product sales and create...time savings with which they can generate sales, enter markets early and grow those markets quickly, and invest in future R&D initiatives.” Greater speed is claimed to lead to the possibility of building brand loyalty, moving down experience curves faster, building channel relationships, and creating switching costs (Schilling and Hill 1998).

We propose that a strong focus on speed and on generating many ideas may actually **hurt** firms, by lowering their conversion ability. By integrating research on problem solving (e.g., Davidson and Sternberg 2003; Duncker 1945), with variables studied in the product development literature, we argue and show empirically that the firms with the highest conversion ability are those that have 1) focus and 2) deliberation in their approach to product development.

Theory

We view the conversion of ideas to new products as a problem solving process (see Davidson and Sternberg 2003; Duncker 1945). In studying conversion ability, our focus is at the most disaggregate level, on the likelihood of conversion of each idea pursued by a firm. We bring together research on problem solving with research on new product development to identify key drivers of conversion ability.

Drivers of conversion

Research on problem solving in psychology and management suggests a number of factors that drive problem solving ability (see Davidson and Sternberg 2003 for a recent review). Four of these factors intersect with variables discussed in the product development context we study in this research. These are: workload, time pressure, expertise, and task importance. **Workload** refers primarily to the number of tasks that are being solved at a point in time (e.g., Bluedorn et al. 1992)¹. **Time pressure** refers to the time within which these tasks must be solved (Karau and Kelly 1992). **Expertise** refers to the domain-specific knowledge that

the problem solver brings to the task (Ericsson and Lehmann 1996). **Task importance** is the value attached to succeeding at a particular task (Sanchez and Levine 1989).

Each of these factors has a correlate in the new product development (conversion) context (also see Cooper, Edgett, and Kleinschmidt 2004; Griffin 1997; Henard and Szymanski 2001; Montoya-Weiss and Calantone 1994). Workload is a direct function of the **number of ideas** that the firm is attempting to convert at any given time. The greater the number of ideas the firm is working on, the greater the workload (Barnett and Freeman 2001). Time pressure is a function of the **speed** with which the firm is attempting to convert ideas into products; the greater the speed, for a given number of ideas, the greater the time pressure on the firm (Kessler and Chakrabarti 1996; Crawford 1992). Firms also differ in the extent to which they have prior **experience** with certain domains or areas of knowledge. The greater their experience with certain areas of knowledge, the greater the expertise they bring to tasks that involve those areas of knowledge. Finally, new product ideas differ in their commercial and technical **importance**; some ideas, if converted into new products, are likely to be major innovations, with huge technical, marketing and financial gains for the firm involved (Hall, Jaffe, and Trajtenberg 2000).²

The above four factors can be integrated under the umbrella of *focus* and *deliberation*, and form the drivers of conversion ability we study in this research. We suggest that the firms with the highest conversion ability are those that focus (on a moderate number of ideas, on ideas of importance, in the firms' areas of expertise) and deliberate (by adopting a moderate level of speed in conversion). We now develop specific hypotheses linking focus and deliberation to conversion ability.

Hypotheses

Deliberation in conversion

Speed of development and conversion ability

Considerable work in psychology and management has examined the role of time and time pressure on problem solving ability in individuals and organizations (see Karau and Kelly 1992; Svenson and Maule 1993). Integrating these disparate findings suggests a non-linear (inverted-U) effect of speed on conversion ability. The inverted-U effect we propose contrasts with that implied in the bulk of the literature on speed in product development, which emphasizes the benefits of increased speed and time pressure (also see

Crawford 1992).

Research in psychology suggests many reasons to believe that *too much* time pressure can hinder problem solving. When time pressure is very great, problem solvers resort to the use of heuristic rather than systematic problem solving, which can result in sub-par outcomes (see Bettman, Johnson, Payne 1991). Moreover, decision makers may ignore crucial information (Bronner 1982), and fail to learn from mistakes (e.g., Luchins 1942). They also tend to emphasize negative information over positive information (Ben Zur and Brezniz 1981), and this emphasis may cause managers to drop projects before they are converted.

On the other hand, research also suggests that *too little* time pressure hinders problem solving (see Svenson and Maule 1993; Karau and Kelly 1992). The literature on organisational decision-making (e.g., Bourgeois and Eisenhardt 1988; Glazer and Weiss 1993) argues that this happens because managers may under-weight the time-sensitivity of information, and also under-weight decisions that are time-sensitive (Glazer and Weiss 1993). Moreover, they may make decisions based on obsolete information (Bourgeois and Eisenhardt 1988). Finally, coordination is likely to be loose and controls lax (Pelz and Andrews 1966). For these reasons, decision makers may lack the urgency needed to concentrate on product conversion goals. Putting these two sets of arguments together, we propose that speed of conversion, and therefore time pressure, has an inverted-U shaped effect on conversion:

H1. Firms with either very high or very low emphasis on speed in product development will have lower likelihood of converting a given idea than those with moderate emphasis on speed.

Focus in conversion

Number of ideas and conversion ability

Having too many ideas may be bad for conversion ability. As with speed and time pressure, prior research on problem solving implies a non-linear (inverted-U) effect of number of ideas on conversion ability (e.g., Barnett and Freeman 2001; Damos 1991). This in turn suggests the importance to firms of focusing on a moderate number of ideas in the conversion process.³ On the one hand, some prior research implies that working on too many ideas at any given time is likely to reduce the conversion likelihood of any particular idea (see Pashler 1994). Capacity sharing explanations for the effect suggest that working on too many tasks simultaneously causes lower attention to any individual task (Navon and Gopher 1979). Bottleneck

explanations argue that when multiple tasks need the same resources at the same time, bottlenecks arise, and all tasks are impaired (DeJong 1993; Pashler 1994). Cross-talk explanations suggest that some tasks may produce outputs or side effects that are harmful to the processing of other tasks (Navon and Miller 1987). The deleterious effects of cross-talk become especially severe as the number of tasks gets larger (see Kinsbourne 1981). Overall, these arguments suggest that processing too many tasks at the same time is likely to lead to lower conversion.

On the other hand, prior research also implies that working on too *few* ideas at any given time can lead to lower conversion ability. Working on too few ideas diminishes the spillovers in knowledge that could arise when several ideas interact (see Irwin and Klenow 1994; Udayagiri and Schuler 1999). Such spillover effects will only exist when multiple ideas are considered simultaneously (e.g., Bluedorn, Kaufman, and Lane 1992; Hall 1983). Integrating these two sets of arguments, we propose that the number of ideas the firm is working on at any given time has an inverted-U shaped effect on conversion:

H2. Firms that work on either too many ideas or too few ideas will have lower likelihood of converting a given idea than those that work on a moderate number of ideas at a given time.

Expertise and conversion ability

The research on problem solving suggests that expertise has a positive effect on conversion ability.⁴ First, experts perceive meaningful patterns that novices miss; specifically, experts can redefine and reclassify problems by noting underlying principles, whereas novices tend to classify problems based on the surface features of the problems (see Chase and Simon 1973). Second, experts use their domain-specific knowledge to implement solutions with greater ease, thus freeing them to concentrate on the effectiveness of the solution strategies (Zimmerman and Campillo 2003). Third, experts have a finer ear for signals (sometimes faint or noisy) received during the problem solving process, and are thus able to monitor performance more carefully. Moreover, they are able to more accurately anticipate the outcomes of actions taken during the problem solving process (Ericsson 2003). They are therefore better placed to determine if the actions are working toward end goals, and to make changes when necessary. Finally, experts tend to be less dissuaded by obstacles, because they are better able to visualize ways around them (e.g., Bandura 1997). Taken together, these arguments suggest that increasing expertise increases a firm's conversion ability. Therefore:

H3. Firms with ideas in their areas of expertise will have higher likelihood of converting these ideas than firms with ideas outside their areas of expertise.

Idea importance and conversion ability

As with expertise, research on problem solving suggests a positive effect of the importance of the ideas the firm is working on and its conversion ability.⁵ This in turn suggests that firms should focus on converting important ideas; firms that do so will have higher conversion ability than those that don't.

Increasing the importance of tasks increases problem solvers' motivation to solve these tasks (e.g., Chaiken and Maheswaran 1994; Zimmerman and Campillo 2003). There are at least three reasons why important tasks are more likely to be completed (Locke 2000). First, task importance regulates the direction of action, by focusing attention and activity on goal-relevant actions at the expense of other actions. Problem solvers therefore make better judgments, and increase the likelihood of successfully completing important tasks. Second, task importance affects the intensity with which problem solvers undertake goal-relevant actions. People put more energy into tasks that are important. They may also receive more positive feedback from others for working on important tasks, relative to working on unimportant tasks. Third, task importance affects the persistence of actions. When faced with important tasks, problem solvers sustain their efforts over time, and do so even in the face of difficulty (LaPorte and Nath 1976). For these reasons, we hypothesize that:

H4. Firms with more important ideas will have higher likelihood of converting these ideas than firms with less important ideas.

In sum: hypotheses H1-H4 predict that firms with the highest conversion ability are those that: 1) *focus* on a moderate number of ideas, of importance, in their areas of expertise, and 2) *deliberate* by adopting a moderate level of speed in product development. Very little research in management has explicitly argued for or tested the predictions implicit in our hypotheses. Moreover, we know of no work in the new product development literature that empirically examines the factors driving conversion ability. To fill this gap, we now turn to an empirical test of our hypotheses linking focus and deliberation to conversion ability.

Method

This section first outlines the empirical context of the paper. It then describes how we obtain measures of the variables of interest to us. It ends with a discussion of the model we specify to test our hypotheses.

Empirical Context

The pharmaceutical industry provides an especially suitable context in which to test our hypotheses. In the US, the Food and Drug Administration (FDA) regulates the pharmaceutical industry closely, documenting every stage of the drug development process. In other countries, equivalent government bodies provide a similar regulatory framework within which pharmaceutical firms operate. The pharmaceutical industry therefore provides a unique source of reliable data on the inputs and outputs of conversion process.

Limiting the empirical context of our study to one specific industry eliminates cross-industry factors as a possible explanation for differences in conversion ability. We do not deny that cross-industry factors may be relevant. However, the focus of this study is on firm-specific differences that cause some firms to convert better than others. Studying one industry helps us focus on this objective, and reduces concerns about internal validity.

Our sample is based on all drug patents from 1980-1985. We obtain this information from the Pharmaprojects database. We examine the primary patents associated with all drugs during our sample period. The total number of such patents is 1573. Of these patents, only 18.30% were eventually converted to drugs, reinforcing our point about the demanding nature of the conversion task. We apply two additional filters to arrive at our final sample. First, we eliminate firms with two or less primary drug patents in the 1980-1985 period. We do this in order to reduce the possibility of conversion due to idiosyncratic events, to focus on firms that have a sustained history of product development, and to be able to account for firm-specific unobserved heterogeneity. Second, we drop patents that were acquired from another firm, whether through licensing or acquisition. We do this because it would be incorrect to draw conclusions about a firm's ability to convert products it did not create in the first place, for at least two important reasons.

First, it is often unclear at what stage the licensor or acquirer obtained the patent (see *Economist* 2004). Thus, it might well be that the patent was acquired or licensed very close to conversion. In such a case, while one could say that the acquirer firm's *picking* ability is high, one can say little about its conversion ability. A related issue is that there are fundamental differences even between licensing and acquisition. The choice of which patents to license is often highly selective, while an acquisition generally

leads to the acquiring firm gaining access to the entire portfolio of the acquired firm, important and unimportant patents alike. As such, comparing conversion abilities across such different samples can be meaningless. Another concern is a practical one; if we were to include licensed and acquired patents, it is unclear which firm should be considered for the purposes of measuring our explanatory variables. Was it the firm that generated the idea and perhaps initiated the process of conversion, or was it the one which finally completed the task? It is hard to see how either choice could be based on anything but subjective criteria.

These filters lead to a sample of 654 ideas developed by 88 firms. However, the need to account for the resource endowments of firms (both, as we note below, as a direct covariate and as a normalizing factor for the number of ideas variable), and the lack of availability of such data further reduces our sample to 322 drug ideas, developed by 38 firms. This is our final sample (for which we have data on all variables of interest). We should note that results on both the larger sample, and the final sample that we report in the rest of the paper, are very similar (albeit with slightly different variables, e.g., the larger sample does not normalize the number of ideas with a firm's resources). Testing our hypotheses entails compiling data on this sample of drugs, and the firms associated with them, from 7 different databases (see Table 1). The following paragraphs describe these in greater detail.

Conversion: We measure conversion as a binary variable, i.e., whether or not an idea (drug patent) was converted to an actual drug launched anywhere on the world market by the end of 2001. We obtain this information from the Pharmaprojects database. This database identifies and monitors the progress of all new drug applications. In particular, it follows each application through the various stages of drug development and testing right up to market launch or discontinuation. We cross-check data from Pharmaprojects by examining FDA approval dates for US launched drugs as reported in the FDA Orange book; the correspondence between these two sources is close to perfect.

The conversion of an idea by a firm deals with the probability that a particular *idea* is converted to a launched drug by the firm. An alternate metric of conversion would be a proportion, between 0 and 1, measuring the number of ideas converted by the *firm*. This seemingly obvious measure, however, suffers from a number of drawbacks. First, the probability of any idea being converted depends on both firm-specific

as well as idea-specific factors. A measure of conversion ability at the level of the firm would not be able to capture any idea-specific factors; such a measure would, if anything, over-emphasize the role of firm-specific factors. Our measure avoids this error, and accounts for both idea-specific as well as firm specific factors. Second, conversion modeled at the idea level is at its most disaggregate; aggregating across diverse ideas and over different time periods risks the introduction of biases that cannot be controlled for.

Speed: This variable measures how quickly a firm moves from an initial product idea to actual product launch. The drug development process is marked by clearly defined stages, ranging from the discovery of a new molecular entity (NME) to pre-clinical and clinical trials to the actual launch of an approved drug (see Figure 1). Each intermediate stage can take varying amounts of time. Since our interest is in the speed from product idea to product launch, and since comprehensive data on the transition of each drug from one intermediate stage to another is unavailable, we do not look at the time taken in each intermediate stage, but consider only the total time taken.

At the level of the individual idea, one can measure speed in a reverse coded manner as the number of days to move from the filing of a patent to the first launch of the product anywhere in the world. This assumes the date of filing of a patent to be synonymous with the birth of a product idea. Clearly, there are other potential ways to identify the birth of a product idea. Ideally, one would want to identify the date of the original flash of insight on the part of the scientist or R&D team involved. Even if one had unlimited access to such people, however, querying them retrospectively is unlikely to produce reliable data. The analogy to academics is illustrative. Which of us can recall the exact (or even approximate) date that an idea for a paper was born? And even if a particular respondent were to remember the date of the birth of a particular idea, it is unlikely we would be able to identify precisely the date of birth of every idea in our sample. People move on, memories fade, and the origins of ideas get lost in the mists of time.

The patent filing date provides an objective measure of the birth of an idea that is readily available to researchers. One criticism of this measure could be that not many ideas are patented. However, this is not the case in the pharmaceutical industry where promising ideas are patented at very high rates, varying from 79.2% in Europe to 95.5% in the US (Cohen, Nelson and Walsh 2000; Arundel and Kabla 1998). Since we

do not observe the date of the original flash of insight, it is important to ensure that the duration from inception to patenting is not excessively large, and that there are no systematic variations in this duration across firms or patents. Dranove and Meltzer (1994, p. 405), who address this point in the context we study, note that: “[I]t seems plausible that .. long times to approval might provide an incentive for firms to delay patent application somewhat in order to postpone the date of patent expiration. We raised this issue with several individuals within the pharmaceutical industry and found no one who was aware of such behavior.”⁶

For all the reasons above, patent filing dates provide a reasonable proxy for the birth of a promising idea in our research context (Dranove and Meltzer 1994). We use the worldwide priority filing date associated with the primary patent for each drug idea as our measure of the birth of an idea. We obtain this data from Pharmaprojects, the Delphion database, and the FDA Orange Book.

While speed can be operationalized in this manner for each individual idea, recall that our interest in testing H1 is to see the impact of a *firm's* focus on speed on its conversion ability. To create a firm-level measure, we examine all drugs launched by a firm in the 20 year period prior to the start of our sample period, i.e., prior to 1980. We calculate the average speed of conversion for all these drugs and call this variable the speed of a firm (we use data on 603 drugs in total to compute speed for our sample).

There are at least two advantages to operationalizing speed in the manner above. First, this helps us get around the problem of measuring speed for ideas that have been abandoned, and thus not converted. Observe that, effectively, such ideas are ‘infinitely slow’, or have a speed of zero. One could solve this problem if one knew precisely when a particular idea was abandoned. Such data, however are almost impossible to find, and where they exist, are extremely noise-prone and subjective. This suggests that a measure of speed at the idea level would be of little use for the vast majority of ideas (around 80%) which do not get converted successfully. Second, by measuring speed using data from a pre-sample calibration period, we avoid the contamination that would be inherent in using the same patents to compute both conversion and firm speed. We also conduct additional analyses with calibration periods that started 15 and 30 years prior to the start of our sample period; our results remain essentially unchanged. To check the robustness of our measure further, we calculated the average firm speed for the period 1980-2000 (using only launched drugs,

needless to say). This measure gives us an average of 9.60 years to conversion, versus an average of 9.47 years for our current measure (which was calculated on a sample 20 years *prior* to 1980). The standard deviation of speed to conversion in the sample period 1980-2000 is 1.62 years, versus 1.73 years in the sample we actually use. Further, we conducted a two-sample t-test to see if the differences between the speed numbers in the period 1980-2000 were significantly different from the ones we use in our estimation. The hypothesis of no difference cannot be rejected at any reasonable significance level ($p > 0.75$). All this gives us confidence that our measure of speed does capture the construct we study.

Number of promising ideas: There are a number of ways to measure the notion of a promising idea. The most obvious way is to ask people actually working in the industry. However, there are a number of problems with such an approach. First, human memory is selective: ideas that were eventually converted are more likely to be viewed, in hindsight, as having been the most promising to start with. The selective nature of memory will introduce a systematic bias into data obtained in this manner. Second, ideas that do not get past a certain minimum stage in the development process are likely to go unrecorded and be eventually forgotten. Third, relying on a subjective interpretation of what is ‘promising’ is likely to be ambiguous. At what stage should the idea have shown promise for it to be rated as such?

To avoid these problems, we use primary drug patents to measure the number of promising ideas a firm is working on converting at a given point in time. As we note above, patents are an excellent proxy for new product ideas in the pharmaceutical context given the extremely high patenting rates in the industry. Moreover, every drug idea has a primary patent associated with it and information on all granted patents is recorded and publicly available, adding credibility and verifiability to our results.

For every idea in our sample, we compute the number of other patented ideas the firm is simultaneously working on from the time the focal idea is first patented to the end of a firm-specific window. This window is equal to the firm’s speed. Thus, if a firm’s speed is 8 years, and the focal idea is patented in 1981, we would consider all ideas that the firm had from 1981 to 1988, inclusive. We construct similar rolling windows for every patent idea for every firm. Further, since large firms are likely to have the capacity to work on more ideas at any one time than small firms, we divide the number of ideas obtained above by a

measure of the firm's resources. We use the log of the firm's assets (more precisely, a 6 year rolling window of the firm's assets) as the normalizing factor. (Analyses using a non-normalized measure of number of ideas yield qualitatively similar results). In the discussion that follows, all references to the number of ideas variable are to the normalized measure of number of ideas. We obtain the information necessary to construct this variable from the Pharmaprojects, Delphion, WorldScope, Million Dollar Directory, Compustat, and Principal International Businesses databases.

Expertise: Drug development is a knowledge-intensive process, requiring high levels of expertise. Therapeutic categories differ greatly, with success in, say, developing drugs to combat diabetes rarely translating to a competitive advantage in developing anti-viral drugs. For example, Merck is renowned for its expertise in cardiovascular ailments, while GlaxoSmithKline is well-known for its expertise in infectious diseases (*Economist* 1998).

The variable of interest to us is the extent to which a firm has prior expertise in the therapeutic categories relevant to the focal patent in question, i.e., the patented idea the firm wishes to convert into a product. To measure this, we first need to measure a firm's expertise. We measure expertise by constructing an array of all the therapeutic categories in which the firm has ideas in development or on the market during our 20-year calibration period (again, 15 and 30 year calibration periods yield similar results).⁷ We use the Pharmaprojects therapeutic classification system to develop this array. The Pharmaprojects classification is a hierarchical system that classifies drugs by the disease area they exert their effect upon. The system covers the entire spectrum of therapeutic areas (there are 197 categories in all) and is specifically tailored to drugs in research and development. We compare the categories of expertise of the firm, obtained using the method above, to the therapeutic categories of the patent itself. We then compute a weighted sum of the overlapping categories using as weights for each category the number of drugs owned by the firm in that category. The higher this number, the greater the firm's expertise that is relevant to the conversion of the focal patent.

Idea importance: A large prior literature has suggested that important ideas can be identified by the number of forward citations they receive: the greater the number of forward citations, the higher the importance of the original idea (Griliches 1984; Jaffe, Trajtenberg, and Henderson 1993). Forward citations

have a precise definition in the patent context—they refer to the number of times the focal patent was cited by other patents. This measure has the following merits. First, it is objective and readily available. Second, market and institutional forces ensure that this number is neither inflated nor understated. It is not inflated because no firm has an incentive to cite another patent if it doesn't have to. In fact, the more patents one cites in one's own patent, the smaller the scope of the monopoly of one's own patent. And this measure is not understated, because the patent examiner checks firms' tendency to understate by ensuring that they cite all patents that represent the prior art. The tension between the incentives of firms not to overstate and the incentives of the patent examiner to guard against understatement ensures that our measure is an accurate reflector of an idea's importance. We obtain the data for this measure from the Delphion database.^{8,9}

There are a number of issues to clarify, however, about the use of our measure of importance. First, forward citations follow a temporal distribution with some heterogeneity. The implication of this is that the number of citations can be greatly influenced by when we choose to measure them. To see this, suppose we have idea A patented in 1980 and idea B patented in 1985, and suppose we measure their importance in 1988. Idea A has had 8 years to collect forward citations, while B has had only 3 years. Even if A and B are equally important ideas, our measure would erroneously identify A as more important. This possible bias arises due to the temporal right truncation of our sample. In our case, we measure citations through 2002, which amounts to a period of more than 17 years. The length of our time period minimizes concerns of bias due to right truncation.

Another issue with our measure of importance is that of reverse causality. Our hypothesis suggests that more important ideas (those that are cited more) are more likely to be converted. It could be argued, however, that it is precisely *because* patents are converted that they are cited more. To see this, suppose patent A was filed in 1980 and converted in 1990. Suppose further that the patent received 10 forward citations by 1990, and 50 citations overall (i.e., by 2002, the end of our sample period). One could argue that the *bump* upwards due to conversion (call it the *bump ratio*) is the ratio of the number of citations *after* conversion, to the number before, i.e., $40/10=4$. If such a bump exists, it would only exist for converted patents; one should find no such bump for patents that weren't converted.

As a check, we compare the bump ratio for converted patents with an equivalent ratio for non-converted patents. For the latter, we use the mean number of years to conversion for the entire sample as the bump cutoff point. If there is a significant bump due to conversion, one would expect the bump ratio for converted patents to be significantly greater than that for non-converted patents. We find this not to be the case: the bump ratios for converted and non-converted are 0.62 and 0.70 respectively.

As a further robustness check, we create another importance measure that adjusts the measure above by the respective bump ratios for converted and unconverted ideas. Essentially, to get a measure ‘uncontaminated’ by the impact of conversion, we need to count citations until the point of conversion. This amounts in essence, to multiplying the forward citation numbers for converted and non-converted patents by 0.38 ($=1-0.62$) and 0.30 ($=1-0.70$) respectively. We find that our results regarding idea importance are robust to this alternate measure of importance.

Control variables: To control for a variety of effects on conversion ability over and above those we hypothesize, we develop a number of control variables.

Novelty of ideas: We measure the novelty of an idea by computing the number of backward citations that the patent associated with the idea uses (Hall, Jaffe, and Trajtenberg 2000). Higher backward citations imply lower novelty.

Country Heterogeneity: There are considerable differences in the drug regulatory environment across countries. There may also exist other, unobserved factors that make it easier to convert drugs in some countries relative to others. In all we have four country-based categories: Japan, U.S., Europe, and Other. We compute an index of each firm’s propensity to launch in a particular regulatory environment by measuring the percentage of previous launches by that firm in each of these country categories. Thus, even though we have four categories, each of the categories is a number between 0 and 1, with the categories summing to 1. For example, if a firm had four products, which it launched first in Japan, the U.S., Europe, and Other respectively, then this firm would have 0.25 as its propensity in each of the country categories. Note that this measure does not refer to the idea in question, since the vast majority of the ideas in our sample have not been launched – the firm level propensity refers to *previous launches* by that *firm*.

Primary Therapeutic Category: It is conceivable that the probability of conversion of an idea might vary significantly across therapeutic categories. To control for such variation, and still preserve degrees of freedom, we use a more aggregate version of the Pharmaprojects classification system than the one we use to develop our Expertise measure. Pharmaprojects employs a system developed by the European Pharmaceutical Market Research Association (EPHRA) to aggregate the entire spectrum of therapeutic areas (197 in all) and create 17 therapeutic groups, each group representing a broad disease area or the body compartment affected (e.g., alimentary, cardiovascular). We operationalize therapeutic categories as 16 dummy variables that correspond to these therapeutic groups.

Resources: We use assets to measure firm resources. Since drug development takes a considerable period of time (on average, 6-10 years), we need to consider the firm's resources not only at the time of idea generation, but also into the future, over the process of conversion. To do this, we create variables with rolling windows. For example, for a patent in 1980, we calculate the average assets of the firm to which the patent belonged, for the 6-year period, 1980-1985. As a robustness check, and to account for the considerable variance in conversion times, we also created 9- and 13-year rolling window measures.

Time: In order to control for the effects of time, we create dummy variables for each of the 6 years that constitute our sample time period, viz. 1980-1985.

Model Specification

Recall that we define conversion ability as a firm's ability to translate a promising idea into a launched product. Our dependent variable, therefore, is dichotomous; namely, whether an idea is converted to a launched product or not. Accordingly, we use a discrete choice specification. Specifically, we use a logit specification. The logit model has been widely used in marketing to model discrete outcomes. Formally, the model specification can be written as (Greene 2000):¹⁰

$$y = 1 \text{ if } y^* > 0 \text{ (i.e., converted)} \\ = 0 \text{ if } y^* \leq 0 \text{ otherwise.}$$

where y^* represents the net benefit of conversion¹¹ associated with product j from firm i in time period t , and is given by:¹²

$$\begin{aligned}
y_{ijt}^* = & \beta_0 + \beta_1 \text{Speed}_{it} + \beta_2 \text{Speed}_{it}^2 + \beta_3 \text{Number_Ideas}_{it} + \beta_4 \text{Number_Ideas}_{it}^2 + \\
& \beta_5 \ln(\text{Expertise}_{ijt}) + \beta_6 \ln(\text{Importance}_{ijt}) + \beta_7 \ln(\text{Novelty}_{ijt}) + \beta_8 \text{Europe}_{it} \\
& + \beta_9 \text{Japan}_{it} + \beta_{10} \text{OtherCountry}_{it} + \beta_{11} \ln(\text{Resources}_{it}) + \sum_{k=12}^{16} \beta_k \text{Time} + \sum_{l=17}^{32} \beta_k \text{Therapeutic_Category}_{jt} + \varepsilon_{ijt}
\end{aligned} \tag{1}$$

Now, the probability of observing a conversion by firm i of product j in time period t is:

$$\Pr(y_{ijt} = 1) = \Pr(y_{ijt}^* > 0) = F(\beta' X_{ijt}) \tag{2}$$

If we assume the ε_{ijt} are distributed with an extreme value distribution, we get the logit specification, with:

$$\overline{L}_{ijt} = \Pr(y_{ijt} = 1) = \frac{\exp(\beta' X_{ijt})}{1 + \exp(\beta' X_{ijt})} \tag{3}$$

The above specification assumes that the parameters are homogenous across firms. However, factors unobserved by us could also affect firm behavior. For example, it is certainly the case that we have not measured managerial ability differences between firms; these, however, could have a significant impact on conversion ability. We can control for such firm-specific heterogeneity by specifying a random intercept. A similar argument could be made for each of the coefficients. For instance, the impact of, say, speed on the probability of conversion might differ across firms. This might be because some firms are better organized to deal rapidly with changing technological conditions, while others are not. These intangible and unobservable processes in fact constitute the heart of firm-specific differences in the resource based view of the firm, and it is vital we account for such differences. We do so by using a random coefficients specification (Revelt and Train 1998). If the parameters β are distributed as $f(\beta | \theta)$, we have:

$$L_{ijt} = \int \overline{L}_{ijt}(\beta) f(\beta | \theta) d\beta \tag{4}$$

Following past literature, we assume that the parameters are distributed as: $\beta \sim N(\overline{\beta}, \Sigma)$, i.e., with mean vector $\overline{\beta}$ and covariance matrix Σ .¹³

The likelihood function is given as: $L_i(\theta) = \prod_j \prod_t L_{jt}(\beta)$ and the log-likelihood function is:

$$LL(\theta) = \sum_i \ln(L_i(\theta)) \tag{5}$$

We estimate our model by maximizing the log-likelihood function above.

Results

Figure 2 presents the distribution of conversion rates, at the firm level, for our full data set. Figure 3 shows the variation within firms of time till launch. Table 2 presents descriptive statistics for time till launch on the basis of therapeutic category. There is also variation within the therapeutic categories – the standard deviation of these durations ranges from 3.6 to 7.9 years. Table 3 presents the maximum likelihood estimates of the logit model described above. The following paragraphs describe the results for each variable.

Impact of Speed: Hypothesis 1 suggests that firms with very high or very low emphasis on speed in product development have lower conversion ability than firms with a moderate emphasis on speed. The results support an inverted U-shaped impact of speed on the probability of conversion ($\beta_1 = 0.38, p < .01$, and $\beta_2 = -0.03, p < .01$). The implication of this result is that the highest probability of conversion occurs for firms who emphasize moderate levels of speed. Figure 4 plots the predicted probability of conversion for different levels of speed, and brings out the inverted U-shape hypothesized. The figure shows a probability of conversion of about 0.23 at the mean level of speed (8.97 years), which drops to about 0.05 as a firm moves two standard deviations below this mean. Finally, note that there is no significant unobserved heterogeneity in the impact of speed¹⁴.

Impact of Number of Ideas: Hypothesis 2 suggests that firms that work on too many or too few ideas have lower conversion than firms that work on a moderate number of promising ideas. The results support an inverted U-shaped impact of number of ideas on the probability of conversion ($\beta_1 = 0.05, p < .05$, and $\beta_2 = -0.03, p < .05$). Similar to speed, the implication of this result is that the highest probability of conversion occurs for firms who emphasize a moderate number of ideas. Recall that this result controls for a firm's resources; therefore the ideas are per unit of resources that the firm has available to it. Figure 5 plots the predicted probability of conversion for different levels of number of ideas, and indicates the hypothesized inverted U-shape. The figure shows a probability of conversion of about 0.23 at the mean level of normalized number of ideas (6.99), which drops to about 0.05 as a firm moves two standard deviations above this mean. Again, note that there is no significant unobserved heterogeneity in the impact of number of ideas.

Impact of Expertise: Hypothesis 3 suggests that firms with ideas in their area of expertise will have higher conversion than others. This hypothesis is supported ($\beta_5 = 0.63$, $p < .01$). Figure 6 plots conversion probabilities for different levels of expertise. The figure shows an increase in the probability of conversion of ideas from about 0.13 to about 0.37 as the expertise moves from two standard deviations below the mean (the log of expertise has a mean of 0.34) to about two standard deviations above the mean. Also, there is no significant unobserved heterogeneity in the impact of expertise.

Impact of Importance: Hypothesis 4 suggests that firms with more important ideas have higher conversion than other firms. This hypothesis is supported ($\beta_6 = 0.54$, $p < .01$). Figure 7 plots conversion probabilities for different levels of importance of ideas. The figure shows an increase in the probability of conversion of ideas from about 0.07 to about 0.51 as the importance moves from two standard deviations below the mean (the log of importance has a mean of 1.59) to about two standard deviations above the mean. Also, there is no significant unobserved heterogeneity in the impact of importance.

Control Variables: A key control variable is the novelty of the idea being converted. Our results suggest that novelty has a significant negative impact on the probability of conversion. β_7 , the coefficient for the number of backward citations (i.e., lack of novelty) is 0.37 ($p < .05$). Second, we also include variables to control for differences in regulatory environments across countries. We find that the probability of conversion is significantly higher for firms that have a propensity to launch drugs in Japan and the Other group, than for firms that have a propensity to launch drugs in the U.S. Third, only two therapeutic categories show significant effects on the probability of conversion – anti-cancer ($p < .05$) and neurological products ($p < .01$). The category excluded from the analysis (i.e., the base category) was cardiovascular drugs. Our results suggest that relative to the cardiovascular category, anti-cancer and neurological drugs have a significantly lower probability of conversion. Fourth, we find one significant time effect; ideas which have 1982 as a priority year seem to have a significantly lower probability of conversion ($p < .05$), relative to the base of 1980. Finally, the resource variable has no significant effect on the probability of conversion, perhaps because we have already partially controlled for it by normalizing the number of ideas by resources.

Discussion

Are some firms better than others at converting inventions (promising ideas for products) into innovations (launched products)? If so, what distinguishes firms with conversion ability from firms that lack it? Despite the importance of these questions, research on conversion is rare, and conversion ability remains a puzzle.

Given the pressures to innovate, many firms have gravitated toward generating larger numbers of promising ideas, and increasing the speed with which these ideas are taken to the market. These managerial practices are supported by a vast literature in new product development on methods to increase idea generation (Sowrey 1987, 1990; Verhage, Waalewijn, and van Weele 1981) and speed-to-market (Choperena 1996; Griffin 1997; Kessler and Chakrabarti 1996). An implicit assumption of both managerial practice and academic research is that more is better and speed is a need for success in innovation. In contrast, we argue and show that a strong focus on speed and generating many ideas may actually **hurt** firms, by lowering their conversion ability. We find that the firms with the highest conversion ability: 1) focus on a moderate number of ideas, in areas of importance, and in areas where they have expertise, and 2) deliberate for a moderate length of time on promising ideas.

Conversion ability appears to have an intuitive, seemingly obvious impact on performance in a variety of contexts (e.g., Gross 1972; Nicholas 2000). For this reason, an underlying assumption of our arguments throughout this paper is that increasing conversion ability is a desirable, indeed profitable objective for firms. Formal tests of this assumption, however, face some practical problems. The efficiency gains that can be derived during the conversion of ideas to launched products appear over a long period, and cannot easily be tied to performance in a particular year.

With this caveat in mind, we conduct a face validity check of the impact of conversion on performance. In the absence of idea-level performance data, we collect data on firms' return on investment (ROI) and compare the performance on this measure of firms with high versus those with low conversion ability in our sample period. We obtain information for this analysis from a number of different sources: Compustat, Pharmaprojects, Worldscope, Principal International Businesses, Kompass and the Million Dollar Directory. Recall that by the end of 2001, close to 99% of the products in our database had either been converted or effectively discontinued. Therefore, we measure performance (ROI) at the end of 2001. We

then compute the partial correlation between ROI in the year 2001 and firm-level conversion rates of product ideas from 1980-1985, measured as continuous percentages, while controlling for firm resources and firm nationality.

We find that the partial correlation between ROI in the year 2001 and firm-level conversion rates is 0.30 ($p < .05$). We also perform a median split on these conversion rates, and classify firms in our sample as being high versus low on this variable. As Figure 8 indicates, firms with high conversion ability have significantly greater average ROI in 2001 relative to firms with low conversion ability (2.60 versus 1.05). This analysis, while far from definitive, provides some suggestive evidence for the importance of conversion ability. Firms that have this ability perform better overall than firms that lack it.

We next discuss the implications of our findings.

Implications for practice

Speed can kill; More ideas can yield less: In contrast to common beliefs and practice, our findings suggest that setting a punishing schedule for the conversion of ideas into products is counter-productive for firms. So too is setting too slack a schedule. The obvious implication for firms is that they should ensure they do not operate at either end of the spectrum on speed, but rather identify the more productive middle ground. In particular, firms that base their new product development programs around achieving time-bound targets may wish to pause somewhat, and allow their personnel to deliberate. Our empirical research on firms in the pharmaceutical industry suggests that in this industry, the optimal speed is around nine years from idea to drug approval. Any speed targets that are set too far below or above this level could be detrimental to the firm's drug development program. Similarly, in contrast to some prevailing beliefs and practice, our findings suggest that working on too many ideas simultaneously is counter-productive for firms. Firms that seek conversion ability may be better off focusing on a moderate number of promising ideas.

Experience counts: We find that firms that focus on ideas in technical fields in which they have expertise are better at converting these ideas into approved drugs than firms that don't. These results imply that conversion is greater when firms stick to their knitting when it comes to new product development.

Idea importance is important: We find that firms that focus on important ideas have higher

conversion ability than firms that don't. The implication of this finding is that managers should, when selecting ideas to pursue, focus on ideas that have important technical and commercial implications. One would expect, of course, that this would be their objective in any case. However, it is not uncommon for firms to pursue ideas that might be incremental and therefore perceived as low risk. The outcome of this, our findings suggest, is that doing so diminishes the firm's likelihood of converting ideas. Important ideas, in contrast to incremental ones, have the advantage of galvanizing employees and motivating them to see the idea fructify into a finished product. Firms that focus on important ideas will enjoy high conversion ability.

Implications for research

Our approach not only enables us to study a phenomenon—conversion ability—that has not been given much research attention, but also allows us to contest some widely held assumptions of the new product literature. For instance, much research on new product development assumes that it is desirable to attempt to bring products to market quickly (see Getz and de Bruin 2000; Kessler and Chakrabarti 1996). This paper is not the first to argue that excessive speed can be harmful (see Bayus 1997; Crawford 1992; Smith 1999). This paper is, however, an early empirical attempt at doing so by using large-scale data. It is also unique in highlighting the impact of speed on an important product outcome: conversion ability. Similarly, much research on new product development assumes that working on more ideas is better (see Sowrey 1987; Verhage, Waalewijn, and van Weele 1981). This paper highlights the deleterious effects of working on too many ideas simultaneously. Our focus on conversion ability emphasizes a key aspect of the new product development process that has not been previously analyzed.

Second, our work complements important aspects of the new product development literature. The literature has frequently focused on the outputs, such as innovative new products, of the product development process. While the output of new products is ultimately the goal of the process, our work highlights the importance of *efficiency* in the process, i.e., outputs relative to inputs.

Third, our results suggest a great deal of variance between firms in their conversion ability. This finding has a direct implication for policy related research. It suggests that average numbers, such as \$802 million for the cost of developing a new drug (see US Congress, Office of Technology Assessment 1993;

also see DiMasi, Hansen, and Grabowski 2003), could be a poor basis for policy making. This number might well be significantly lower, for example, for firms that focus on a few ideas in their areas of expertise. In recent years, the pharmaceutical industry has come under heavy criticism for the high prices it sometimes charges for lifesaving drugs that consumers in many parts of the world can barely afford (Scherer 1993). Critics also note that many of these drugs are based on publicly-funded research, that firms' expenditure on salesforce activities is greater than that on R&D, and that the industry has been extremely profitable for the last two decades or so. The argument that drug companies use in their defense is that: 1) drugs cost huge amounts to develop and 2) if firms are not assured of recouping these costs (by pricing high) they would not have the incentive to develop these drugs in the first place. A crucial input in this argument is the cost of drug development. The numbers presented are often based on average development costs and conversion rates across firms. Our research suggests that firms vary in their conversion ability; some firms are more efficient than others at converting ideas into drugs. Researchers may wish to consider this variance when formulating policy prescriptions.

Ours is among the first papers on conversion ability. As with many early papers in a research area, our research has a number of limitations, some of which could provide fruitful avenues for future research. For example, it would be interesting to see more evidence on the performance implications of conversion ability, such as the quality and performance of the products that are converted. The ROI-based evidence we offer here, while confirmatory, is clearly limited.

Second, it would be useful to systematically examine the generalizability of our research by studying conversion ability in contexts other than the pharmaceutical context. One can think of generalizability along various dimensions. Efficiency in converting inputs to outputs is likely to be desirable in many new product development contexts, much beyond the pharmaceutical context. The theoretical underpinnings of the paper, as they relate to the impact of constructs such as focus and deliberation on conversion, should also be fairly generalizable across industries. However, the measures used may not be as generalizable. In particular, patents and product launch may not have the same significance in other contexts as they do in pharmaceuticals. Other inputs (e.g., development expenditures) and other outputs (e.g., product sales) may be

more relevant in other industry contexts. Third, we have not examined a number of alternative strategies that firms could follow, e.g., focusing on novel drugs which have a low conversion probability but a large payoff. Examining these issues would need financial data on each converted drug. Similarly, it is possible that some firms are good at picking ideas (through acquisition or licensing) whereas other firms specialize in inventing good ideas that they then seek to convert. We do not address the extent to which different types of firms pursue either or both of these strategies. We leave the exploration of these and related questions to future research.

Finally, our arguments on deliberation and focus highlight the importance of attention and consideration in conversion ability. Research that examines these and other behavioral underpinnings of conversion in more detail (for example, by more explicitly measuring the consideration and attention process in firms) would be very valuable. Survey data, in particular, would be helpful in this regard.

Table 1: Variables and Data Sources

Conceptual variable	Measure	Data source
Conversion	Conversion of patented ideas to launched drugs	Pharmaprojects FDA Orange Book
Speed	Number of days from patenting of drug idea to drug approval (reverse coded)	Pharmaprojects FDA Orange Book
Number of promising ideas	Number of primary drug patents owned by the firm, normalized by log(assets)	Pharmaprojects Delphion
Expertise	Overlap in therapeutic areas between patented drug and firm's drug portfolio (# drugs in area)	Pharmaprojects
Idea Importance	Total number of forward citations for patented drug	Delphion
Control Variables	<p>Idea Novelty: Total number of backward citations for patented drug (reverse coded)</p> <p>Priority Country Primary Therapeutic Code</p> <p>Resources (rolling window)</p> <ul style="list-style-type: none"> • Net income • Net Sales • Assets • R&D Expenditures 	<p>Delphion</p> <p>Pharmaprojects Pharmaprojects</p> <p>Worldscope COMPUSTAT Million Dollar Directory Principal International Businesses</p>

Table 2: Variation in Time Till Launch by Therapeutic Category

Therapeutic Category	Mean Time till Launch	Standard Deviation
Alimentary	8.74	3.90
Blood/Clotting	9.50	3.63
Cardiovascular	10.82	4.31
Dermatological	9.56	4.80
Formulations	10.56	4.03
Genitourinary	9.44	3.43
Hormonal	9.88	3.62
Immunological	15.25	7.93
Anti-infective	8.54	3.71
Anti-cancer	9.50	4.29
Musculoskeletal	9.50	4.08
Neurological	11.02	5.01
Anti-parasitic	9.89	5.23
Respiratory	8.96	3.82
Sensory	15.50 ^a	13.44
Biotechnology	16.00 ^b	0.00
Miscellaneous	7.71	4.11

^a: Based on two products only

^b: Based on one product only

TABLE 3: Results of the Logit Model Estimation

Dependent Variable: Probability of Conversion

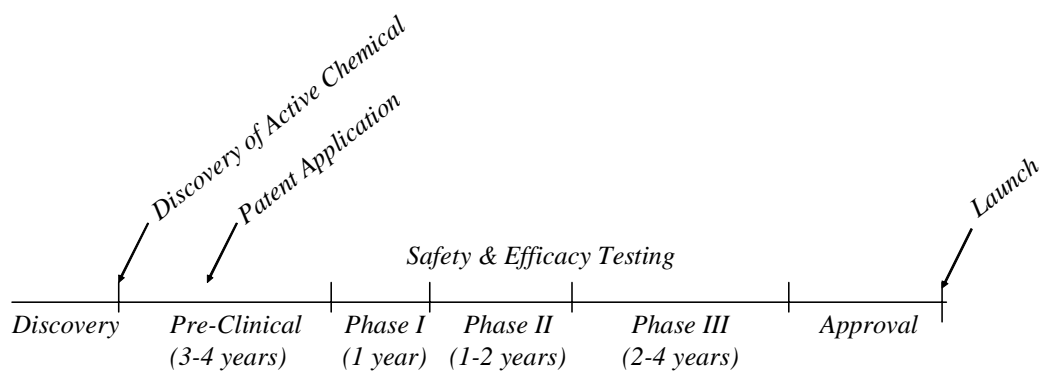
Variable	Coefficient	Standard Error	Unobserved Heterogeneity	Standard Error
Constant	-3.53 ^{***}	0.75	0.07	0.12
Speed	0.38 ^{***}	0.16	0.01	0.13
Speed ²	-0.03 ^{***}	0.01	0.05	0.14
NumIdeas	0.05 ^{**}	0.03	0.03	0.24
NumIdeas ²	-0.03 ^{**}	0.02	0.00	0.00
Expertise	0.63 ^{***}	0.23	0.13	0.17
Importance	0.54 ^{***}	0.10	0.03	0.05
Novelty	0.37 ^{**}	0.16	0.18 ^{**}	0.07
Europe	0.41	0.34	1.16 ^{***}	0.29
Japan	1.08 ^{***}	0.34	0.03	0.18
Other country	1.55 ^{**}	0.69	0.19	0.60
Resources	-0.18	0.15	0.02	0.10
Time 1981	0.31	0.44		
Time 1982	-0.87 ^{**}	0.43		
Time 1983	-0.58	0.45		
Time 1984	-0.27	0.36		
Time 1985	-0.26	0.43		
Alimentary	-0.85	0.54		
Blood/Clotting	-0.82	0.55		
Dermatological	-0.73	0.82		
Formulations	20.25	21455.63		
Genitourinary	-0.03	0.93		
Hormonal	-0.09	0.82		
Immunological	0.79	1.27		
Anti-infective	0.14	0.34		
Anti-cancer	-1.05 ^{**}	0.53		
Musculoskeletal	-0.85	0.64		
Neurological	-1.48 ^{***}	0.55		
Anti-parasitic	-20.47	21265.50		
Respiratory	-0.55	0.56		
Sensory	-18.14	14916.09		
Biotechnology	0.12	0.53		
Miscellaneous	0.50	0.73		

Likelihood value = -143.59

$\chi^2 = 38.42$ (p<.05)

* p<.10; ** p<.05; *** p<.01

Figure 1: The Drug Development Process



Adapted from: Office of Technology Assessment (1981); FDA (1999); Mathieu (2002)

Figure 2: Distribution of Conversion Rates

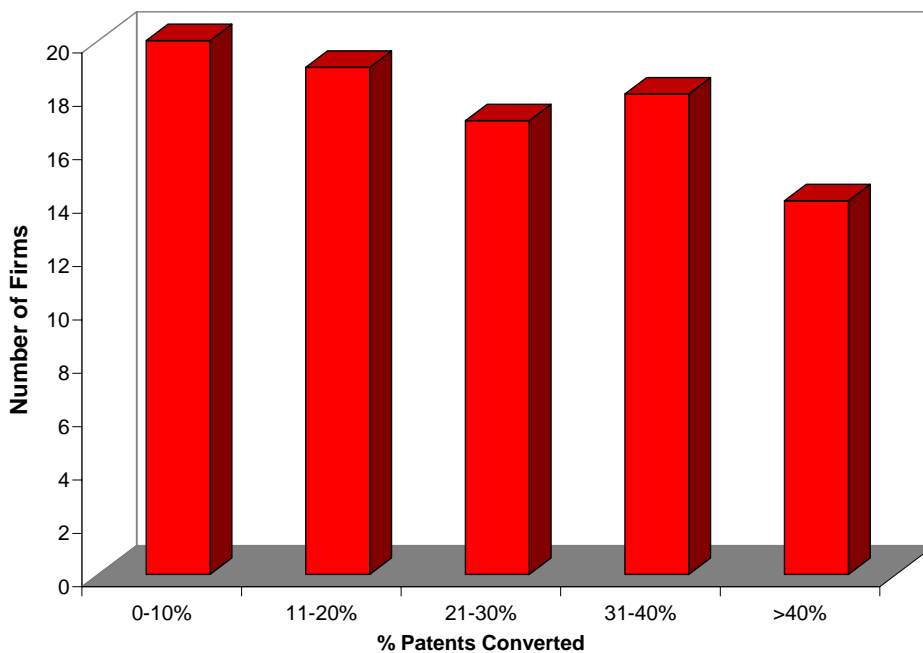


Figure 3: Variation within Firms in Time Till Launch

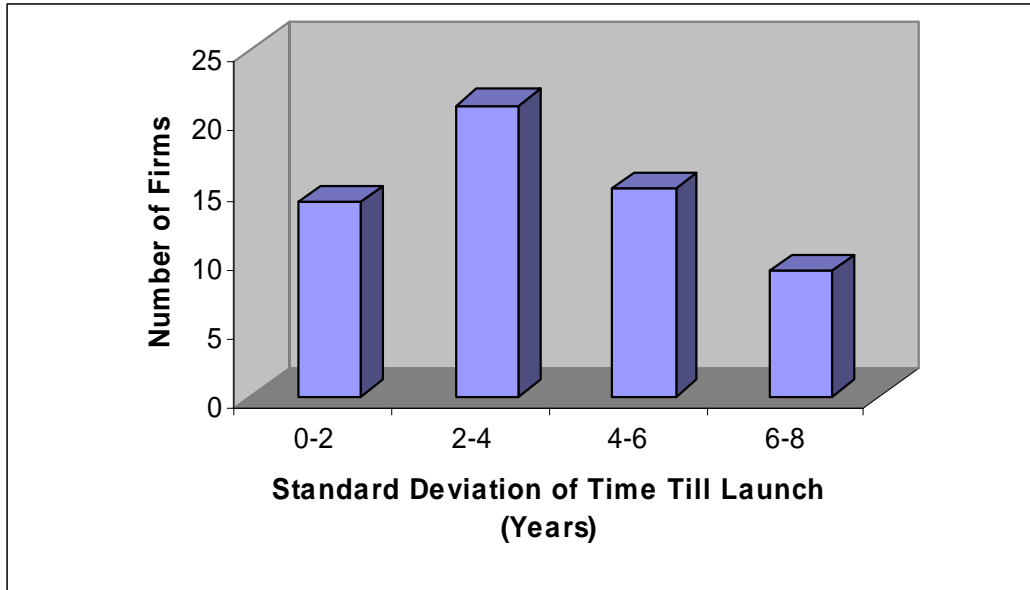


Figure 4: The Impact of Speed on Conversion Ability

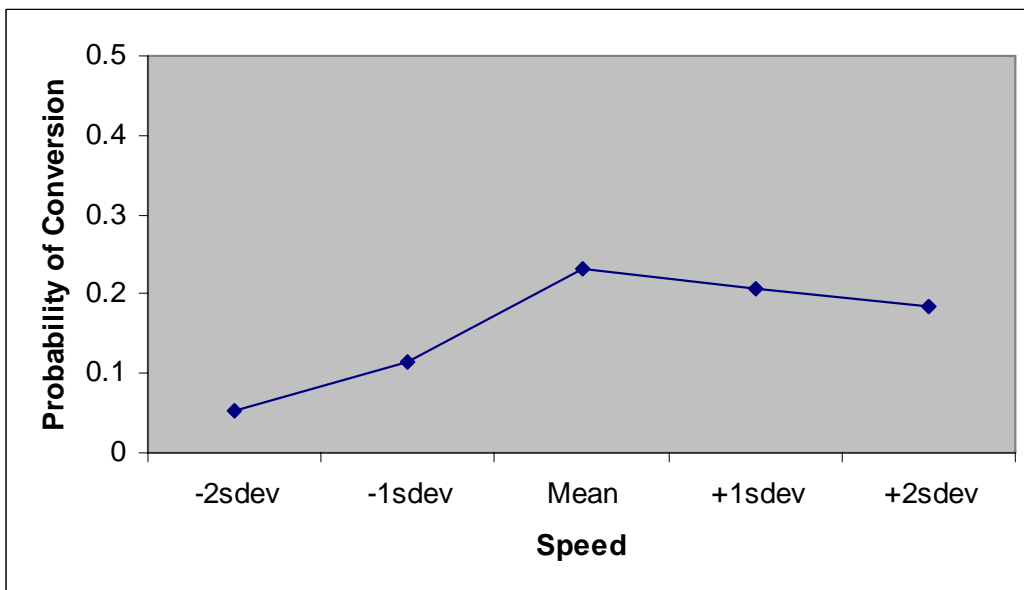


Figure 5: The Impact of Number of Ideas on Conversion Ability

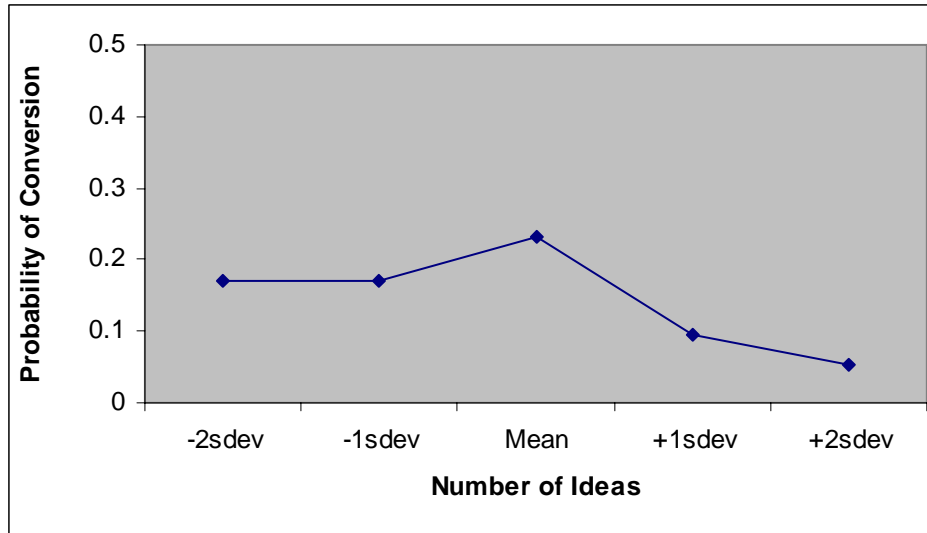


Figure 6: The Impact of Expertise on Conversion Ability

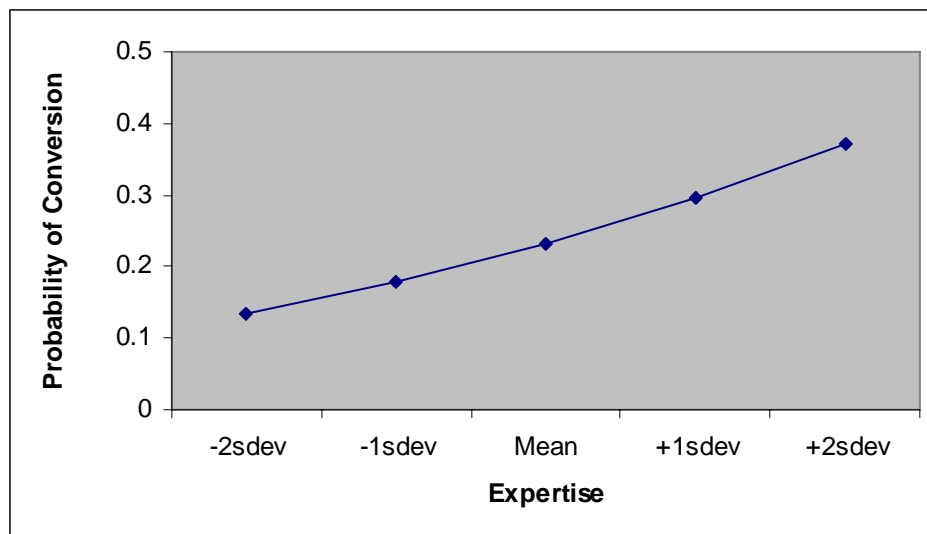


Figure 7: The Impact of Importance of Ideas on Conversion Ability

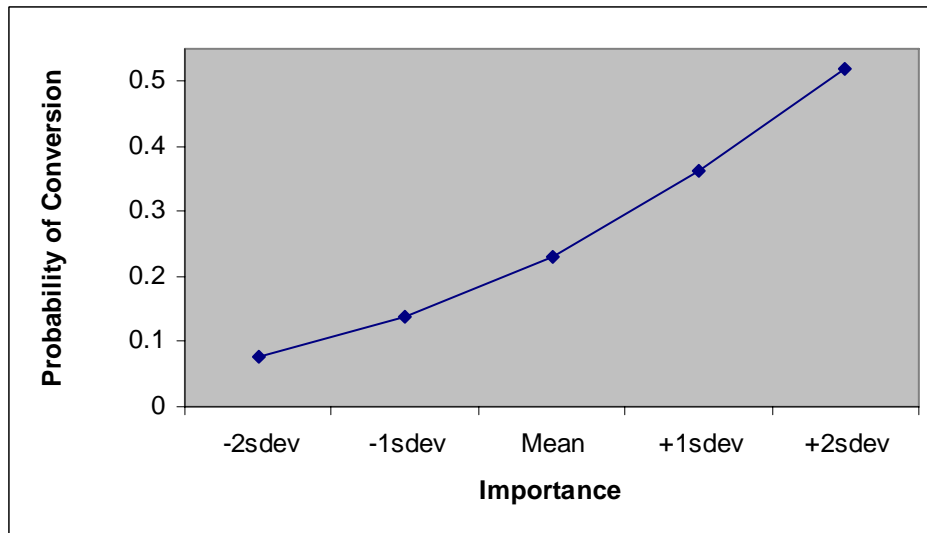
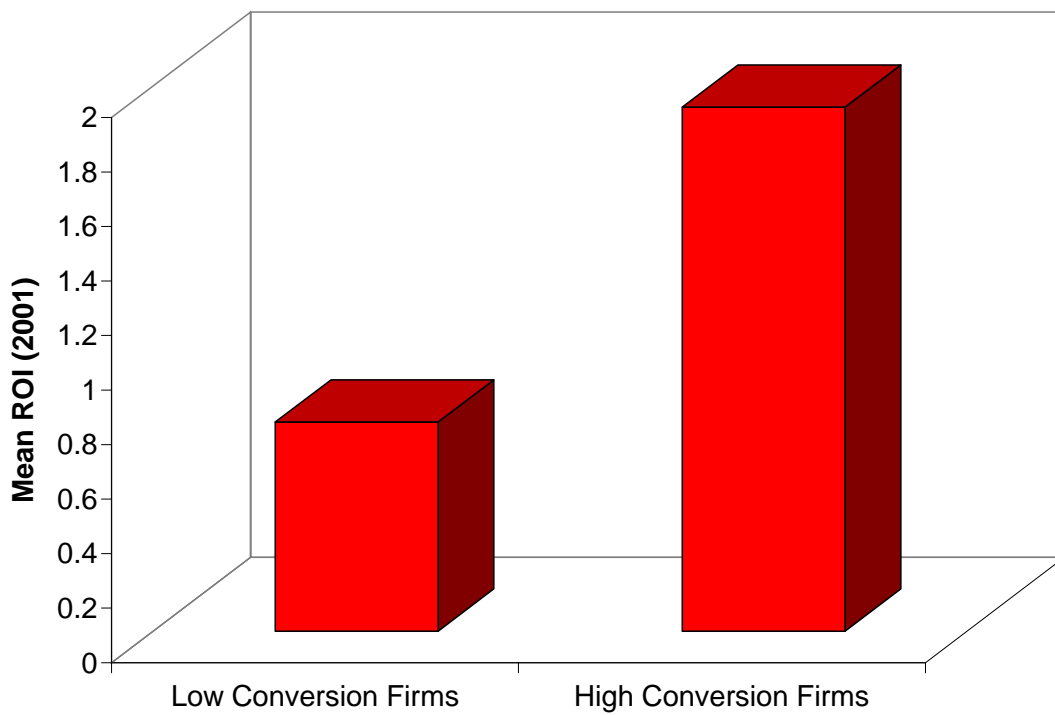


Figure 8: The Impact of Conversion Ability on Financial Performance



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ENDNOTES

¹Some research treats workload as including time pressures. For the sake of analytical clarity, we treat time pressure as a separate factor driving problem solving success.

²One could argue that firms do not know exactly how important an idea is eventually going to be. We agree. At best, firms can make an educated guess about the expected value of an idea. In the absence of any compelling evidence to the contrary, we make the parsimonious assumption that there are no systematic biases across firms in their assessment of an idea's importance.

³Since the optimum number of ideas for a firm is likely to vary by its size, we control for this empirically by scaling our number of ideas variable by firm size in our empirical test. Throughout our conceptual discussion, we use "number of ideas" to mean this number per unit firm size.

⁴We note that expertise is related to incumbency, a variable of considerable strategic importance in the innovation literature. To be consistent with the problem solving literature, we use the term expertise, while noting that our results on this variable have relevance for work on the relationship between incumbency and innovation.

⁵Importance is a complex variable that potentially includes technical, market and financial dimensions. Conceptually, we do not make a distinction between these dimensions; rather, we assume that they all cause firms to behave similarly with respect to the conversion task.

⁶It is possible, however, that ideas vary in the extent to which they need work and time to be converted into products. We acknowledge that our measure does not control for this variance. We also acknowledge that firms sometimes patent for defensive reasons: to throw off competition and develop options on a compound for the future.

⁷We acknowledge that this measure of expertise ignores the types of process skills that firms may have for commercializing patents. Such skills would be captured in the unobserved heterogeneity component of our empirical model, which we describe later.

⁸One potential drawback of this measure is that forward citations are available *after* the fact, while importance, in our conceptualization, has a role at the time the idea is patented. One can think, however, of the firm (and other interested parties) as having *ex ante* conjectures about the importance of an idea. It is reasonable to suppose that the firm's conjectures are, absent systematic bias, likely to be closest to the true mean, which our measure represents.

⁹An ideal measure of importance would be to measure the amount invested in converting each idea. Unfortunately, it is practically impossible to get this information, especially given the longitudinal nature of our data, and given the wide array of firms in our sample.

¹⁰One possible complication here, given the nature of our dependent variable, could be the presence of right-censoring, i.e., it might be that an idea is still in the process of conversion, and cannot really be counted as 'not converted.' We examined our data closely, and determined that only 7 drugs in our sample (1.07% of the total) were still in the pre-clinical or clinical trials stages at the end of our study period (2001). As such, right-censoring is not a major issue, and we do not account for it in our model.

¹¹This is the counterpart of "utility" in standard consumer choice models.

¹²Our specification aims to be as general as possible, while conforming to our theoretical arguments. The quadratic specification for the speed and number of ideas measures are dictated by theory, while the logarithmic specification for the other variables is to ensure generality. We thank the Editor for suggesting this specification.

¹³Please note that the unobserved heterogeneity is over firms, i.e., one could write each β as β_i and define the distribution of the β as above.

¹⁴We also examined if the factors associated with focus - number of ideas, expertise, and selection of important ideas - drive speed, and if speed (measured contemporaneously) mediates the impact of focus on conversion. We found no such effects.