

# On the origin of technological acquisition strategy: The interaction between organizational plasticity and environmental munificence\*

Luis A. Rios<sup>†</sup>

**Abstract:** Why do some firms routinely acquire more than others? I add to extant theory on technological acquisitions and M&A learning by documenting how the interaction between organizational plasticity and environmental munificence can create one demarcation point for some technology firms to become more acquisitive than others. Using a novel dataset on 1,201 firms that went public between 1983 and 2007 I find evidence of a persistent divergence even twenty years after IPO. Additional tests rule out alternative explanations and explore potential mechanisms.

**JEL Classification:** D23 D83 L22

**Keywords:** Plasticity, R&D, Technological Acquisitions

---

\*This study was funded in part by Wharton Dean's Research Fund. I am indebted to my advisors Ashish Arora, Sharon Belenzon, Wes Cohen, Ronnie Chatterjee, and Dan Levinthal for patient and excellent guidance. Many thanks to Deborah Anderson, Nicholas Argyres, Emilie Feldman, Exequiel Hernandez, and Nicolaj Siggelkow for helpful comments on various drafts of this paper. Thanks also to seminar participants at Stanford M&E, London Business School, Wharton, Berkeley-Haas, INSEAD, Washington University-Olin, Georgia Tech-Scheller, NYU-Stern, Duke-Fuqua, and UNC-Kenan-Flagler.

<sup>†</sup>Wharton School of Business, University of Pennsylvania. 3620 Locust Walk Philadelphia, PA 19104. [luisrios@upenn.edu](mailto:luisrios@upenn.edu)

## 1 INTRODUCTION

Incumbents in innovative industries often expand their knowledge base by buying smaller and younger firms. Such “technological acquisitions” (Ahuja & Katila, 2001) are increasingly being used even by non-technology firms in the pursuit of competitive advantage,<sup>1</sup> and have motivated an important literature at the intersection of mergers and acquisitions (M&As) and innovation. But while this channel should appeal to most firms trying to lower the risk of internal research (Henderson & Cockburn, 1996; Dierickx & Cool, 1989), it is accessed robustly only by a subset of them. For example, Cisco Systems, Google, and Johnson & Johnson have a reputation for getting much of their technology externally, while Nvidia and Netflix favor internal innovation. More systematically, a recent study of over one thousand American corporations found persistent and bimodally distributed differences in the degree to which they relied on these acquisitions (Arora, Belenzon & Rios, 2014), suggesting some type of sorting towards either strategy.

Four gaps in our theories of technological acquisition—and M&A more broadly—preclude a satisfactory explanation for why we observe these differences. First, since technological acquisitions exploit knowledge embodied in targets, most prior work has focused on the complementarity between parties’ knowledge bases (Ahuja & Katila, 2001; Sears & Hoetker, 2014; Grimpe & Hussinger, 2014) and to a lesser degree on post-acquisition integration choices (Puranam, Singh & Zollo, 2006; Barkema & Schijven, 2008). However, these are primarily dyadic deal-level constructs which do not take into account the determinants or consequences of acquirers’ long-run patterns of acquisition. Second, most samples used in the literature are conditional on realized acquisitions, and thus silent about differences between those that do and do not acquire on a regular basis. Third, while the broader acquisition learning literature has paid much attention

---

<sup>1</sup>In 2016, non-tech companies bought more tech companies than ever before. According to Bloomberg, 682 technology firms were purchased by companies in an industry other than technology, while 655 businesses were purchased by pure-play technology companies <https://www.wsj.com/articles/every-company-is-now-a-tech-company-1543901207>

to the link between prior acquisition experience and future deal performance, many of the motives and challenges related to M&A broadly writ<sup>2</sup> differ from those in technological acquisitions, limiting generalizability. Fourth, even if prior deal experience on average helps with future technology deals, this would be a somewhat circular explanation for the question of *why only some firms end up honing this type of skill in the first place*. In other words, at some point all new firms lack acquisition experience,<sup>3</sup> and then some accumulate it and others do not. These lacunae are not surprising since most work has looked at firms acquisition behavior “mid-stream” in firms’ histories (Helfat & Winter, 2011), so we know little about the antecedents of technological acquisitiveness itself.

In this study I provide one such antecedent by theoretically arguing and empirically showing that the interaction between organizational plasticity and environmental munificence can create one demarcation point for some technology firms to become more acquisitive than others. Plasticity is a relatively underexplored construct within the organizational learning literature, broadly conceptualized as a firm’s ability to adapt to its environment and move beyond its current template of capabilities, routines, or activities (Gavetti & Rivkin, 2007). But this is a time-varying property, likely highest at founding and declining with age (Amburgey & Miner, 1992) once rigidities (Leonard-Barton, 1992), routines (Nelson & Winter, 1982), and interdependencies (Siggelkow, 2011a) arise. On the other hand, environmental munificence—the magnitude of opportunity that a business seeks to exploit (Castrogiovanni, 1991)—varies unpredictably as a result of macroeconomic and industry cycles (Dess & Beard, 1984; Staw & Sz wajkowski, 1975). The core argument of this paper is that firms with more plasticity during munificent times for technological acquisition will be more likely to make this channel a part of their regular repertoire in the long run.

I test the implications of this argument using a novel dataset which details the technological acquisition activity for all innovative manufacturing firms that went public between 1985 and

---

<sup>2</sup>For example: empire building, hubris, diversification, coordination. See (Haleblian, Devers, McNamara, Carpenter & Davison, 2009) for a review of M&A motives.

<sup>3</sup>I address the potential role of founders’ prior experience in sections 2.2. and 3.2.5.

2007. This is an ideal setting because IPOs increase organizational plasticity (Stuart & Sorenson, 2003) while at the same time sharply increasing incentives to acquire. All firms in my sample are by construction more likely to be plastic by virtue of having gone public, so I exploit variance in the time they spend under munificent environments to test whether the joint effect of organizational plasticity and munificence is correlated with future acquisitiveness. While I do not seek to establish causality, I provide a descriptive analysis and potential explanation for a puzzling and economically significant empirical regularity, yielding several contributions. First, it adds to our understanding of R&D and innovation strategy by providing large-scale evidence of the role of persistent firm heterogeneity in technological acquisition activity, highlighting the importance of looking beyond deal-specific characteristics. Second, it raises the possibility that the technological acquisition channel, which has traditionally been thought of as a way to avoid the path-dependency of internal development (Dierickx & Cool, 1989; Puranam, Singh & Chaudhuri, 2009), may itself be constrained and path-dependent. Finally, it adds to our broader theories of organizational learning by showing how the combination of temporary plasticity and shifting opportunity sets may put firms on different trajectories early on in their lives, serving as a demarcation point for persistent heterogeneity.

## **2 PRIOR LITERATURE AND THEORY**

### **2.1 Technological acquisitions**

Technological acquisitions involve targets (often small and/or young) that bring embodied technological knowledge (Ahuja & Katila, 2004; Puranam et al., 2006). In many cases, developing new technologies internally is sub-optimal due to the challenges of innovation, such as time compression diseconomies (Dierickx & Cool, 1989), hard-to-observe quality, and unpredictable lags between inputs and outputs (Arrow, 1962). Buying realized technologies in the market for firms mitigates some of the uncertainty, while introducing a set of trade-offs. Acquisitions of any type incur costs and risk associated with target selection (Capron & Mitchell, 2009), negotiations (Jemison & Sitkin, 1986), and integration (Haspeslagh & Jemison, 1991). Additionally, technological acquisitions tend to disrupt the “technological subsystem” (Thompson, 1967) of the firm

and the innovation routines of both acquiring and acquired firms. They also face what Puranam et al. (2006) term an “organizational dilemma”: acquirers must integrate acquired firms in order to build on their technologies, but must also preserve some of the organizational autonomy of targets in order to avoid disrupting their innovative capacities (Puranam & Srikanth, 2007; Ranft & Lord, 2000).

The challenges discussed so far have driven much of the research in this sub-field. However, we know much less about why the external channel seems to appeal more to some firms than to others. This is because most studies use *deal-level* measures which do not take into account the determinants or consequences of acquirers’ long-run patterns of acquisition. While some work has included measures such as the count of prior acquisitions (e.g. Puranam & Srikanth (2007)) it has not been as a main dependent or independent variable, but more often as a control or moderator. Second, most samples used in the literature are by construction conditional on *realized acquisitions*, and so they focus on performance differences between different types of deals or (to a lesser degree) different types of acquirers, rather than on the differences between firms that do and do not acquire on a regular basis. In sum, it is surprising that, given the importance of knowledge itself for technological acquisitions, little work has explicitly looked at the role of acquisition learning in conditioning firms’ reliance on technological acquisitions.

## 2.2 Acquisition learning

Can a simple learning process explain why some technology firms rely so much on acquisitions? I argue that this is unlikely. The question of how firms develop acquisition expertise and capabilities has preoccupied a number of scholars at the intersection of organizational learning and M&A (Hayward, 2002; Zollo & Singh, 2004; Cuypers, Cuypers & Martin, 2017). Here, “learning” is generally conceptualized as the effect of prior acquisition experience through an accumulation of knowledge (tacit or codified) within the organization, or through changes in the organization’s activities, routines or structures (Cyert & March, 1963; Levitt & March, 1988; Zollo & Winter, 2002). But the relationship between experience and performance has been found to be compli-

cated. Unlike operational settings, where the accumulation of experience has predictable benefits along learning curves (Argote, 1999), acquisitions are characterized by factors that hamper reinforcement learning. Buying another firm consists of many interdependent tasks, each of which is complex in itself (Hitt, Harrison & Ireland, 2001). Also, no two targets or deals are ever alike and each transaction requires idiosyncratic processes—especially when the goal is to combine knowledge bases. Thus it is hard to codify knowledge or generalize from prior experience (Zollo & Singh, 2004), resulting in causal ambiguity (Lippman & Rumelt, 1982). As discussed in the prior subsection, these challenges are likely to be exacerbated in the case of technological acquisitions.

But even if we were sure that prior deal experience on average helps with future deals, it would be a circular explanation for the question of *why* only some firms end up honing this type of knowledge in the first place, since all firms lack acquisition experience at founding, yet but some go on to accumulate it and others do not. Of course the argument can be made that some *de novo* firms may start off with some pre-existing experience embodied in their founders (Kimberly, 1975; Boeker, 1989; Fern, Cardinal & O’Neill, 2012) and that this individual-level knowledge could be transferred to the organization. However, much work has shown that the type of tacit knowledge involved in acquisitions resides within organizational routines, and is hard to transfer or codify (Zollo & Winter, 2002). This makes it unlikely that a founder can “teach” its start up how to do technological acquisitions, much in the same way that a consultant cannot do the same for a client firm.<sup>4</sup> Therefore, it is likely that factors besides experience itself should account for at least some of the difference between acquirors and non-acquirors.

### 2.3 Plasticity and path-dependency

The concept of *organizational plasticity* can shed light on the foregoing question. Within management and organizational studies, the word “plasticity” has been used at various levels of analysis, often colloquially, to connote some antonym to rigidity. For example, features of organizations are said to be plastic if they are flexible (Levinthal & Marino, 2015) or if they are socially defined

---

<sup>4</sup>Potential confounds from founder effects and similar pre-history are mitigated empirically in Section 3.2.5.

or can adapt to local circumstances (Weick, Sutcliffe & Obstfeld, 2005). Within institutional theory, it has been described as the ability to modify boundaries (Fox-Wolfgramm, Boal & Hunt, 1998) or to undergo reversible temporary accommodations (Lok & De Rond, 2013). At the individual-cognitive level, concepts of neural plasticity have even been invoked to explain the role of heuristics (Bingham, Eisenhardt & Davis, 2007). Surprisingly, there has been little effort to formalize what plasticity is beyond simple non-rigidity, to incorporate it into our theories of organizational learning and change, or to explore it empirically.

I argue that a sharper conceptualization of plasticity is useful in exploring the origins of technological acquisition strategy. Webster's definition of plasticity includes: "the ability to retain a shape attained by pressure deformation," which neatly encapsulates the tension between change and stability that is central to organizational learning. The emergence of stable routines and capabilities at once enable the reliable performance of activities (Helfat & Winter, 2011) while ossifying parts of the organization, limiting the choice of future activities (Nelson & Winter, 1982; Cyert & March, 1963). And so keeping the sequential/temporal features of plasticity explicitly in mind, I follow the narrower definition advanced by Gavetti & Rivkin (2007), who view it as an organization's ability to change elements of its strategy, *but only within limits and within a limited time-frame*. Over time, they point out, cognitive and physical elements that make up a strategy become less plastic, which makes a firm's early adaptive choices potentially path-dependent (David, 1992, 1985) or at least to some extent "sticky" (Szulanski, 2009; von Hippel, 1994). With age, firm maturation then brings about a phalanx of forces that chip away at the flexibility of youth: Stable routines emerge (Nelson & Winter, 1982), cognitive inertia sets in (Tripsas & Gavetti, 2000), specialized assets are bought (Williamson, 1975), and complex interconnected activity systems arise (Siggelkow, 2011b).

It is critical to note that the foregoing conceptualization is distinct from the notion of strict "imprinting" as used in population ecology (Stinchcombe, 1965; Hannan & Freeman, 1977). That view assumes such inflexibility that it is a central mechanism in the culling of less-fit organizations,

for whom changing a core feature exposes them to great risk of mortality (Hannan & Freeman, 1984). On the other hand, organizational plasticity can be seen as a rather “weak form” of imprinting (Levinthal, 2006), as it results from stability that is girded by rational mechanisms such as the dynamics of increasing returns and chaotic processes (Arthur, 1996; Baum & Amburgey, 2001; Vergne & Durand, 2010). While these imprints also carry a stamp from prior adaptive responses and firms’ starting positions on the search landscape, they are sustained so long as the practices and structures in place satisfy the organization’s search efforts—and are discarded before becoming an existential liability.

## 2.4 Testable Proposition

Concatenating the foregoing, I argue that heterogeneity in firms’ reliance on the external channel may be the observable manifestation of early firm plasticity interacting with more (less) munificent environments for such deals. Technological acquisitions alter the resource base of the organization and are challenging activities to execute reliably. And so a young firm in a state of high plasticity should find it easier to modify its nascent routines and structures around the new-to-the-firm activity of acquiring and absorbing targets. These *ad hoc* (Helfat & Winter, 2011) initial attempts at buying technological targets may lead to the emergence of routines, capabilities, activity systems that are tailored around acquiring. For example, it may develop incentive systems for R&D managers that address the “not invented here” problems (Katz & Allen, 1982) and reward both visionary and incremental researchers fairly (Stern, 2004), it may cultivate deal sourcing, due diligence and negotiating talent (Higgins & Rodriguez, 2006; Trichternborn, Knyphausen-Augfseß & Schweizer, 2016), and overall set up its structure to be “coherent” with regard to acquisitions (Arora et al., 2014). Conversely, similarly plastic firms that do not face a good set of opportunities to acquire may get “locked-in” prior to having developed such a strong a predilection for the external channel. Given the descriptive nature of my study and its large sample, it is beyond the scope of this paper to parse out which mechanism (e.g. routines, learning, capabilities) is more likely to perpetuate the predilection for acquiring or not. In the next sections I look for evidence consistent with these arguments and rule out alternative explanations.



### **3 METHOD, DATA, AND MEASURES**

#### **3.1 Empirical Setting: Why newly IPO firms should be plastic and at-risk to engage in technological acquisitions**

My empirical examination faces three challenges: First, no prior work has attempted to quantify or measure plasticity; second, measuring firms' acquisitiveness calls for sampling on the dependent variable—it is hard to know who is at-risk of acquiring, and acquiring is an endogenous firm choice; third, plasticity is highest at founding and decays quickly thereafter, making the systematic study of acquisitions under plasticity difficult (because young firms seldom acquire due to resource constraints (Celikyurt, Sevilir & Shivdasani, 2010)). I therefore exploit two features of the initial public offering (“IPO”) process which help mitigate these concerns.

First, while we cannot directly observe plasticity at the firm level, we can make reasonable assumptions about when firms might on average be plastic. Undergoing an IPO should increase firm plasticity even many years after founding (Stuart & Sorenson, 2003; VonEije, DeWitte & VanderZwaan, 2013), as the abrupt shift from private to public ownership disrupts many of the rigidity-sustaining mechanisms discussed in the previous section. During an IPO, firms undergo a restructuring of their entire ownership and control structures, incorporate new financial reporting systems, often establish new routines, incentives, and hierarchical structures.

Second, IPOs have also been shown to put firms at-risk to acquire, which mitigates the second concern. IPOs provide firms with previously unavailable reputational and financial capital alongside new strong incentives to grow fast, often through acquisition (Celikyurt et al., 2010; Bernstein, 2015). For example, using a panel of 2,400 US high-tech companies (Carpenter & Petersen, 2002) find that IPO proceeds are generally as large or larger than all of the firm's total assets, and that firms grow rapidly after going public: the median firm's assets triple five years after the IPO, and employment grows by 70% relative to the year of the IPO. Technological acquisitions are also particularly sensitive to the “courtship” between buyer and seller, as most potential targets are controlled by founder-owners who value dimensions other than absolute price, such as the long-term fit and prospects within their new parent (Graebner & Eisenhardt,

2004). These targets will be more attracted to acquirers who have already survived past the IPO.

In all, the foregoing arguments are somewhat circumstantial, yet it is reasonable to assume that on average, newly public firms should regain some of the plasticity of young firms, while shedding their liability of newness and prior resource constraints.

### 3.2 Data

I construct an inventory of patents, inventors, firm structure, and M&A activity for almost all innovative manufacturing firms that listed in major American stock exchanges between 1983 and 2007. I draw on several sources: (i) patent information from USPTO and the OECD's PATSTAT database; (ii) ownership structure data from ORBIS by Bureau vanDjik (BvD); (iii) merger and acquisition data from Thomson SDC Platinum and Zephyr by BvD; (iv) S-1 Regulatory filings from the Securities and Exchange Commission (SEC); and (v) accounting information from COMPUSTAT; (vi) IPO data from Jay Ritter at the University of Florida; (vii) hand-collected searches to identify small technological acquisitions that do not appear in traditional databases; (viii) information on venture capital funding from Thomson VentureXpert, Crunchbase, and manual searches. Detailed description of variables and construction follows. *Table 1* reports descriptive statistics and bivariate correlations for the variables used in the study.

\*INSERT TABLE 1 HERE\*

#### 3.2.1 Independent variable: How economic downturns create variation in opportunity sets

My independent variable *Months\_post* captures the temporal exposure to environmental munificence. It is calculated as the number of months between a firm's IPO and the beginning of the next economic recession as calculated by the Federal Reserve Bank of St. Louis.<sup>5</sup> I limit the

<sup>5</sup>Smoothed recession probabilities for the United States are calculated using a dynamic-factor markov-switching model applied to four monthly coincident variables: non-farm payroll employment, the index of industrial production, real personal income excluding transfer payments, and real manufacturing and trade sales (Chauvet,

sample to firms that went public up to 60 months before the next recession. Figure 1 visualizes both the recessionary periods used in the study and the methodology for calculating *Months\_post*.

\*INSERT FIGURE 1 HERE\*

The logic is as follows. A post-IPO firm may find itself suddenly willing *and able* to buy, being flush with cash and legitimacy. However, it still needs a munificent environment with a robust pool of targets and a healthy level of liquidity in the markets for it to be able to transact. Environmental munificence, the level of resources in a particular environment (Dess & Beard, 1984), affects not just the level of firm survival and growth (Hannan & Freeman, 1977) but also the manner in which firms grow (Bradley, Aldrich, Shepherd & Wiklund, 2010; Staw & Szwajkowski, 1975; Cyert & March, 1963). I therefore exploit variation in the length of time that firms spend in “good” environments after their IPO. I argue that those firms with more time to participate in the active acquisition market encounter more opportunities to develop path dependency in acquisitions.<sup>6</sup>

Indeed, a robust literature has shown that environmental munificence for M&A activity is highly correlated with the overall strength of the economy. One accepted explanation is that firms use inflated stock to buy smaller private firms, or take advantage of differential rates of stock overvaluation to effectively buy at a discount (Shleifer & Vishny, 2003). Additionally, general liquidity and market optimism tends to drive investment (Harford, 2005). As a result, M&A activity occurs in waves which follow the business cycle, usually ending unexpectedly in response to the same macroeconomic shocks that hit broader markets and dampens liquidity and confidence (see also Mitchell & Mulherin (1996); Ball, Chiu & Smith (2011)).

Since firms chose the timing of their IPOs, I do not make a strong claim about this variable

---

1998). Available at <https://fred.stlouisfed.org/series/RECPROUSM156N>. Results are robust to using NBER manually coded dates for recessions.

<sup>6</sup>Clarysse, Bruneel & Wright (2011) make an analogous argument, focusing on environmental dynamism rather than munificence, due to data limitations. Using case studies of six technology companies, they find that the environment indeed moderates future growth trajectories through the accumulation of resources during the first five years of a firm. They did not, however, examine persistence.

being perfectly exogenous. However, I do make the assumption that firms cannot predict *ex ante* when a downturn will come, and therefore the number of months that they spend in active M&A markets after their IPO is not a choice, but rather driven by unforeseen shocks in the future and other firm-specific factors that determine optimal IPO timing, such as the state of their technology, performance, or market share. In a study that supports the assumption, Ball et al. (2011) explicitly test the “market timing hypothesis” of whether firms going public can predict hot markets. Using a sample of 8,163 venture-backed companies, they find evidence of “pseudo-timing,” where firms can spot the signs of a run-up to a wave, but are unable to anticipate when the wave ends.<sup>7</sup> I limit the study to firms that went public during non-recessionary periods, because going public is a choice and we cannot compare firms that IPO during hot and cold periods, as they may have very different reasons for going public<sup>8</sup>.

### 3.2.2 Firm information.

I use COMPUSTAT for financial information. Additionally, I use the Bureau vanDjik (BvD) ORBIS database to map firm structure for the sample.<sup>9</sup> Many firms have complex corporate structures which makes it difficult to draw the boundaries of the firm, for example when trying to identify acquisitions by wholly-owned subsidiaries. Firm financial information is harmonized across COMPUSTAT and BvD. Information on IPO companies and dates comes from Jay Ritter’s publicly available data (Ritter & Welch, 2002) supplemented with COMPUSTAT and BvD to add missing dates of incorporation data to account for mergers, acquisitions, and restructurings, which sometimes cause discrepancies between the company identifier at IPO and the financial time series data used in my panel. In all there are 1,201 IPO firms in the sample. The mean number of IPOs is 53 per year (SD 47).

---

<sup>7</sup>Nonetheless, in Section 4.2.1 I also perform instrumental variable analyses to mitigate endogeneity concerns.

<sup>8</sup>As (Celikyurt et al., 2010) put it: “one of the most important benefits of an IPO is that it improves the ability of the company to make acquisitions,” so a company going public during a cold M&A market may be *ex ante* disinterested in acquiring.

<sup>9</sup>See Chang, Kogut & Yang (2016) and Albino-Pimentel, Dussauge & Shaver (2018), for recent work utilizing ORBIS corporate ownership information.

### 3.2.3 Patent data

I match all patents, applications, and reassignments between 1950 and 2014 for the sample firms, their wholly owned subsidiaries, and their acquisition targets. I build on the European Patent Office (EPO) Worldwide Patent Statistical Database (“PATSTAT”)<sup>10</sup> as a starting point. A collaboration between the EPO and BvD from 2010 to 2013 facilitated progress in matching PATSTAT patents to BvD’s corporate ownership database.<sup>11</sup> However, the merged BvD-PATSTAT data are still relatively noisy and cross-sectional, and do not reliably capture ownership at the time of either IPO or patent filing (BvD updates data daily, which hampers archival studies). Thus these data required considerable adjustment. In order to clarify ownership, I used PATSTAT’s legal event database (which includes the entire USPTO reassignment database plus legal events from several other jurisdictions) to verify ownership of each patent. BvD company-patent records required corrections for about 35% for the whole sample, and as much as 70% for smaller firms, some of which are completely missed by BvD.<sup>12</sup>

### 3.2.4 Dependent variable: Technological acquisitions

Ultimately, the extensive matching of patents to firms is necessary to identify the type of technological acquisitions that are consistent with my theoretical argument. While there is some latitude in what the literature defines as a technological acquisition, I incorporate criteria that are consistent with, and more restrictive than, prior seminal work. First, I limit the sample to targets that have at least one patent. This follows Ahuja & Katila (2001), who also included non-patenting targets based on media mentions, but who had no size criteria. Second, I restrict the sample to targets smaller than 50% of the acquirer in terms of both patents and assets held,

---

<sup>10</sup><https://www.epo.org/searching-for-patents/business/patstat.html>

<sup>11</sup><https://www.idener.es/?portfolio=imalinker>

<sup>12</sup>For example, US7970240B1 issued in 2011, is part of a family of patents protecting Google’s Picasa photo archiving technology. It would seem to have been generated by Google, who is listed the “Assignee” on the face of the patent. However the provisional application behind that family (No. 60/339,804) was filed in 2001, three years before Google bought and absorbed Picasa. Protocols at the USPTO resulted in dropping all records of Picasa as the original owner of the IP. Such transfers in the period between application and grant are common, and as documented by Gans, Hsu & Stern (2008), can lead to under-reporting the scope of external technology.

a relative cutoff similar to Puranam et al. (2006). Given my theoretical arguments about the challenges of technological acquisitions and their integration, I focus on targets that are both likely to be sought for their technology *and* integrated, rather than kept as part of a conglomerate or holding company. This mitigates other synergistic motives, as might be the case in some of the size-agnostic targets included by Ahuja & Katila (2001). I acknowledge the concern about a smaller sample due to excluding non-patenting targets, and potential systematic differences between patenting and non-patenting technological acquisitions. On the other hand, there is compelling evidence that patenting by small and young firms is strongly associated with better financing outcomes (Hsu & Ziedonis, 2013); thus it is likely that the omission would result in an attenuation bias and towards less generalizability for lower quality targets (which themselves may be bought for reasons other than integration, such as fire sales).

I first use both Thompson Reuters SDC Platinum and BvD's Zephyr databases to identify all acquisitions made by my sample firms, then match these targets to their patents. However, in many cases small deals do not appear in any of these databases, so a manual web search was performed for any set of more than five patents owned by a sample firm but showing a different original assignee (which could be either a purchase of patents or of a patenting firm). This yielded over 1,200 additional small targets for the sample, which totaled 5,835 acquisitions over the period 1985-2013. The importance of a detailed inventory of patents for both acquirers and targets has been emphasized by prior studies (Ahuja & Katila, 2001; Higgins & Rodriguez, 2006), and to date most studies of technological acquisitions have been limited to small samples. The main dependent variable for estimations is *Tech\_Acq*, a dummy that takes the value of one if the firm engages in at least one technological acquisition that year.

### 3.2.5 Controls for unobserved pre-IPO heterogeneity

Differences in mature firms might trace back to unobserved pre-IPO heterogeneity—their “pre-history” (Helfat & Lieberman, 2002). Firms may have different pre-IPO orientation in terms of their internal vs. external technology strategy, or may have higher(lower) quality *ex ante*, which

may be correlated both with their IPO timing and with their subsequent acquisition behavior. However, private firms do not report financial information, making it difficult to mitigate confounds due to pre-IPO heterogeneity beyond simple age. Patents provide useful information—for example, if patenting and acquiring are partial substitutes (Cassiman & Veugelers, 2006), firms that are able to patent more may need to buy less. Alternatively, patenting may be correlated with quality (Hsu & Ziedonis, 2013), which may itself correlate with the ability to acquire. I therefore include as controls targets' pre-IPO citation-weighted patent counts, average number of non-patent citations, average originality, and average generality.

Second, in order to mitigate the concern of unobserved heterogeneity in acquisition capabilities, founder experience, or intentions (Eisenhardt & Schoonhoven, 1990; Fern et al., 2012), a team of research assistants read the full S-1 filings of 620 firms (not all filings are available online from the SEC). Each form was read in its entirety by two people, who coded for firms' M&A experience prior to IPO, and for explicit mentions of whether acquisitions played a part of their pre- or post-IPO strategy. While this proxy does not allow me to observe detailed founder characteristics, I argue that the decisions made in the first few years of the firms' life reveal founder preferences and should be a reasonable proxy. The composite measure generated was included as a control. Details of the coding and methodology can be found in the online appendix.

### **3.2.6 Controls for post-IPO characteristics**

Not surprisingly, prior research in the broader M&A literature has found that many firm characteristics, such as size and performance, are correlated with acquisitiveness (see Haleblan et al. (2009) for a review). Thus firms that IPO earlier may simply end up being larger, or have more assets for other reasons, which would explain them doing more deals later.<sup>13</sup> To mitigate such spurious correlations, which would call into question the plasticity and path-dependency logic, I control for the number of employees, firm age (measured from incorporation to observation year), and assets. Employees and assets are logged in regressions. A firm's internal research is also likely

---

<sup>13</sup>I thank an anonymous reviewer for pointing out this alternative explanation.

to affect its technological acquisition efforts (Arora et al., 2014; Cassiman & Veugelers, 2006), so I include acquirers' citation-weighted patent stock (only for internally generated patents) and the log of R&D spending.

## 4 EMPIRICAL APPROACHES AND FINDINGS

### 4.1 Approach 1: Nonparametric evidence of divergence

I begin by splitting the sample in half, and coding firms as *Early* or *Late* based on whether their IPO fell within the first or second half of each non-recession period. The expectation is that, on average, firms would have engaged in fewer technological acquisitions as the number of months between IPO and recession decreases. However, simply plotting each group's rate of acquisition before and after IPO would be confounded by a number of factors, which we cannot control for here (but do so in the next section). For example, differences might be driven by how large the IPO was since firm valuations vary tremendously, in which case more tech acquisitions might simply be a factor of more equity. Or it may simply be due to differences across industries or years. I therefore instead calculate the fraction of new patents that come to the firm from technological acquisitions, relative to their total flow of patents. Because internal development is the primary way to generate new knowledge, and because it is very capital intensive, this provides a convenient baseline to see if firms are becoming more acquisitive *relative to their pre-IPO selves* as they begin to deploy their IPO proceeds and pursue growth.

$EPAT_{ij}$  is each firm's monthly count of external patents and  $IPAT_{ij}$  is the monthly count of internal patents. I use application dates for internal patents because application is the first observable measure that captures R&D investment (Hall, Jaffe & Trajtenberg, 2001), and date of acquisition for external patents. For  $n$  firms  $i$  in each month  $j$ , the sample average external share  $ES_j$  is computed as:

$$ES_j = \frac{\sum_{i=1}^n \frac{EPAT_{ij}}{EPAT_{ij} + IPAT_{ij}}}{n}$$



Figure 5 plots the share  $ES_j$  separately for early and late firms. I center time periods so that we can look at all firms in relation to their IPO date, shown as value 0 on the horizontal axis. By construction, a similar plot (not shown) of the internal share would simply be the plot of  $1 - ES_j$ .

\*INSERT FIGURE 2 HERE\*

We can see that before IPO, early (dashed line) and late (solid line) firms have very similar shares: on average about 5% - 7% of all firms' patents come from acquisition. After IPO,  $ES_j$  increases more starkly for early firms, showing that patents acquired through technological acquisitions accounted for over 15% - 17% after around three years post-IPO. Conversely, for late firms the share hovered around 10% - 12% around the same period. Though not controlling for any covariates, the pattern in the data is consistent with my baseline expectations: 1) all firms increase their share of external-to-internal patents shortly after IPO; 2) early firms do so more markedly; 3) this divergence seems to persist and remain steady over the observation period.

#### 4.1.1 Approach 2: Parametric evidence of persistence in divergence

I next specify a set of cross-sectional Probit regressions exploring the relationship between the main explanatory variable *Months\_post* and the categorical dependent variable *Tech\_acq*, looking for evidence of persistence in this relationship STATA command `probit`. If indeed we are dealing with path dependency consistent with the plasticity arguments, rather than just a temporal adjustment, then we ought to see the divergence between early and late firms continuing into the future, rather than attenuating and reverting to the mean as might be expected by a diffusion process (Cockburn, Henderson & Stern, 2000). Time series fixed-effects models would be inappropriate since my main explanatory variable does not vary over time within a firm, and because I am interested in showing how the correlations between among the variables of interest change (or not) over time. All specifications include the full set of pre- and post IPO firm-level controls described in section 3.2.5 and 3.2.6, as well as and three-digit NAICS industry controls.

By construction, these observations occur at various calendar years for the sample firms, so year controls are included.

Looking at *Table 2*, a number of interesting results are worth discussing. First, the coefficient on *Months\_post* holds relatively steady as we move from three years post-IPO ( $\beta = 0.0090$ ,  $p < 0.000$ ) to 21 years post-IPO ( $\beta = 0.0104$ ,  $p < 0.042$ ). This is consistent with the non-parametric evidence on *Figure 2*. Not surprisingly, due to truncation we see the number of firms observed drop as we increase the length of time between IPO and measurement, which might explain the increase in p-values in later years. Probit coefficients estimate  $\beta/\sigma$ , so their magnitudes are in units of the standard-deviation of the errors—not quite amenable to intuitive interpretation. Thus I estimate and plot predicted probabilities at five-month intervals for the variable *Months\_post*, using the `margins` command in STATA, and observed at three-year intervals post-IPO. *Figure 3* shows the marginal effect of additional distance in months between IPO and recession. The relationship is slightly curvilinear and increases over time as the firm ages, which is inconsistent with attenuation and supports the theory of initial plasticity followed by path-dependency. *Figure 4* shows a surface plot that makes the intuition even clearer (using ten cross-sections). We can see that the predicted probability of engaging in at least one technological acquisition per year ranges from about 24% - 37% in year 4 and the gap between those firms with short and long exposure to munificent environments grows to about 15% - 45% in year 20. It bears noting that, as shown in *Figure 3*, the 95% confidence intervals become increasingly wider both with age (x axis) and with *Months\_post* (z-axis), which warrants some caution about the interpretation of the surface plot at extreme values.

\*INSERT TABLE 2 AND FIGURES 3 and 4 HERE\*

#### 4.1.2 Alternative Explanations and Covariates

Having shown these baseline patterns, I proceed to address the covariates discussed in section 3.2.6, which may be correlated with IPO timing or impact acquisitiveness. In *Table 3* I progres-

sively introduce each of the post-IPO firm-level control variables. I use the same cross-sectional specification as in the prior tests, with full sets of controls for both pre- and post-IPO characteristics and industry and year. All seven models are cross-sectional, observing firms on their tenth year post-IPO.<sup>14</sup> An overview of the table shows that the coefficient on *Months\_post* strengthens steadily as the additional controls are added.

\*INSERT TABLE 3 HERE\*

The sign and pattern of coefficients is consistent with the argument that the relationship between our IV and DV is not driven by the covariates. Looking more closely, we can see in Model 1 a statistically significant coefficient on *Months\_post* ( $\beta = 0.0094$ ,  $p < 0.000$ ), conditional on industry, year, and pre-IPO covariates. This decreases somewhat with the addition of *Employees* on Model 2 ( $\beta = 0.0087$ ,  $p < 0.000$ ). Age *per se* does not seem to matter much in any of the models, which is consistent with results in *Table 2*, where the coefficient on age varied erratically each year, suggesting that other time trends such as year and years post-IPO are more important. Not surprisingly, assets soaks up any impact from employees on Model 5 ( $\beta = 0.1290$ ,  $p < 0.000$ ), suggesting that employees matter primarily as a proxy for firm size in the prior models. Models 6 and 7 show an interesting pattern that calls for future work: while patents are positively associated with technological acquisitions, R&D expenses are not, but together they seem to slightly strengthen the coefficient on *Months\_post*. One speculative explanation might be that technological acquisitions partially substitute for R&D expense as an input into the firms' patent production function, and more so for firms with longer periods between IPO and recession. Finally, and consistent with prior work in the broader M&A literature, sales—like assets—has a strong correlation with acquisitions ( $\beta = 0.1290$ ,  $p < 0.041$ ), though in the prior model this was not the case for every year.

---

<sup>14</sup>Results hold for other years.

## 4.2 Robustness Tests

In the prior tests I take steps to control for as many pre-IPO characteristics as possible, and exploit the unpredictability of economic downturns. However, with such a large sample there is always a risk that unobserved heterogeneity may be biasing the results. Therefore, I perform the following robustness checks.

### 4.2.1 Approach 3: Instrumental Variable Analysis

I employ an instrumental variable regression framework to mitigate the concern that self-selection into the timing of IPO may drive the results. My instrument is the “fund vintage” of the main venture capital (“VC”) investor. The choice of this instrument was based on both its conceptual relevance and its technical suitability (Wooldridge, 2010). Its implementation followed the most current guidelines for identifying, implementing, and interpreting instruments (Bettis, Gambardella, Helfat & Mitchell, 2014; Semadeni, Withers & Trevis Certo, 2014).

Fund vintage (used interchangeably with “fund year”) is the year a venture capital fund had its first capital call (Kaplan & Lerner, 2010; Kerr, Lerner & Schoar, 2011); in other words, it dates the beginning of the fund’s active life. A convenient feature of VC financing is that a) it is prevalent in the funding of technology firms, and b) most funds have a predetermined life, typically 10 years (Gompers, 1996). Prior work has found that finite fund duration influences the timing of key decisions made by VCs. In our setting, it is likely that firms in an older fund will be under more pressure to IPO as soon as market conditions meet a certain threshold, in order to return limited partners’ investments with a profit. Conversely, a firm funded by a younger fund can afford to take a chance on waiting for either the good environment to get even better or for its performance to improve. Consistent with this argument, Dutta (2016) found that firms funded by an older fund took fewer risks. Vintage age should satisfy the exclusion restriction because it is (negatively) correlated with my main explanatory variable *Months\_post*, but there is no reason to expect that the vintage of the fund would be correlated with my dependent variable

or its residuals, since the VC will have no involvement in the ongoing operation of the firm after IPO.

In order to calculate fund vintage,<sup>15</sup> I restricted the sample to IPOs that had a clearly identifiable lead investor. I used a variety of sources to supplement VentureXpert,<sup>16</sup> the leading database on VC investments. Identifying the venture capital investors for our sample firms was facilitated by a recently released Linked Data API wrapper which allows for the automated searching of the CrunchBase data (Färber, Menne & Harth, 2018; Dalle, Den Besten & Menon, 2017) In addition, a team of RAs read through news articles and the S-1 filings to look for mentions of venture capital investors, especially those with seats on the firm's board. As in the specifications in *Table 1*, the year reported is 10, but the results are robust to analyzing other years.

Column 1 reports the baseline Probit regression, showing  $\beta = 0.00887$ ,  $p < 0.031$ , which is a bit weaker than on the results on *Table 1*, and likely due to the smaller size of the sample. I then employ two IV methodologies that are suitable for my binary dependent variable with a continuous endogenous variable. Column 2 reports the results of our first IV specification using the `eprobit` function in STATA 15, which implements a maximum likelihood estimator following (Wooldridge, 2010). For additional robustness, *Column 3* replicates the model using a minimum chi-squared estimator (Newey, 1987), invoked with the `twostep` option for STATA's `ivprobit`. Results of both approaches are very similar and mitigate the concern that self selection into IPO timing is a factor in driving the association between timing and future acquisitiveness. *Column 4* reports the first stage for *Model 3*, showing that Vintage Year is negatively correlated with *Months\_post*. Finally, Column 5 reports the results of a full model regressing our main DV *Tech\_acq* with the IV (*Vintage Year*) as the explanatory variable. Consistent with my theoretical arguments about satisfying the exclusion restriction, vintage year is not correlated with technological acquisitions.

\*INSERT TABLE 5 HERE\*

<sup>15</sup>In keeping with prior work, when first capital call date is not available, first investment is used.

<sup>16</sup><https://vx.thomsonib.com/VxComponent/vxhelp/VEglossary.htm>

### 4.2.2 Additional Tests

In unreported specifications, I check the robustness of my results by restricting the sample to exclude firms that went public in the first and last two months of a non-recessionary period, in order to mitigate the unlikely concern that firms have private information that allows them to predict the beginning or end of economic cycles. I also successively remove firms that went public during individual non-recessionary periods (e.g. excluding firms that went during the last wave, the one before that, etc.). Results are not much different for these specifications, except for the expected impact of smaller sample size on coefficients.

## 5 DISCUSSION AND CONCLUSIONS

This study adds to our understanding of technological acquisitions by exploring the relationship between IPO timing and firms' subsequent technological acquisition patterns. While prior literature has explored the role of organizational learning on M&A performance—that is, whether and how firms learn to acquire (Haleblian et al., 2009; Zollo & Meier, 2008; Trichternborn et al., 2016), with an emphasis on deal-level variables—my project calls attention to the importance of *when* firms begin to acquire and how this might influence long-run behavior. I expand the conversation by considering the role of time-dependent organizational plasticity as a moderator in the relationship between experience and performance.

For technological acquisitions, we know that the ability to utilize this channel at the very least has to involve a set of systems that allows for the frequent recombination of the firm's critical knowledge base. I have argued that the sort of change needed to be able to begin engaging in technological acquisitions is more feasible during periods of heightened plasticity. By limiting the study to firms that begin acquiring while in a transition period from private to public (and hence likely to be more plastic), I am able to show circumstantial evidence in support of the relationship between plasticity, the environment, and a path-dependent reliance on technological acquisitions. Firms that go public further away from the next recession seem to engage in more technological acquisitions well into maturity, and this effect actually strengthens over time, rather

than attenuate as one might expect if it were a simple response to a temporary shock. While this study is agnostic as to the microfoundations that maintain such path-dependency (e.g. learning, capabilities), future work should explore more focused tests of predictions from our current theories of learning, routines, and capabilities viz. these patterns.

My findings are also informative to managers, who must constantly “discriminate between what is and is not controllable” (Gavetti & Levinthal, 2004). Thus the present study is helpful in highlighting a novel factor that firms might consider in assessing their constraints to change. For example, firms that grow up in times of depressed acquisition markets may have tougher internal obstacles to overcome along the way of adopting an acquisition strategy, such as entrenched roles and compensation structures that reward internal development. These may not be as responsive to a top-down decree for different strategy, which may partially explain why some firms seem to struggle with acquisitions despite great efforts and repeated attempts.

From the perspective of younger firms, my findings could inform decisions about IPO timing and how to nimbly respond to reversals in capital markets. For example, while I looked only at firms going public during non-recessionary periods, my findings could be useful for firms considering an IPO during a down market. If a firm has particularly strong internal research opportunities and does not expect to rely on acquisitions, then an off-cycle IPO may actually have some benefits in terms of reduced competition for scientific talent. Finally, IPOs are not the only process that can disrupt core features of the organization. Mergers and demergers, when large enough, might also make firms plastic. Therefore, firms undergoing such transformations may need to consider the economic environment as it may have unintended effects on the direction of a firm’s growth after a transformative event. Conversely, these events may be (counter-intuitively) a good time to implement other deep changes to the organization in order to capitalize on the plasticity.

As discussed earlier, I do not seek to establish causality through the estimations in this study. However, I seek to document a set of conditional correlations that have not been explored in

the literature to date, and to assess whether they are consistent with the theoretical arguments developed. I also use an empirical design that makes alternative explanations less likely. The goal is to inform both theory development and future empirical work. Because the study focuses solely on both buyers and targets that engage in patenting, we must be cautious in generalizing these findings to the general population of firms. Future work should explore whether similar patterns are found for non-technological acquisitions.

I contribute to recent work that has shown persistent heterogeneity in the activities that support R&D (Arora et al., 2014), as well as broader work that has shown the importance of firm fixed effects in explaining heterogeneity in acquisition strategy and performance (Golubov, Yawson & Zhang, 2015). More broadly, my findings shed light on the question of how firms set about doing things they have never done before, especially when the task is difficult and complex like technological acquisitions. These activities call for capabilities well beyond operational efficiency, and we are just beginning to explore how these capabilities arise. At some point what starts as an “ad hoc” effort becomes routinized in a way that is performed reliably and predictably (Helfat & Winter, 2011), a process that likely necessitates the modification of routines and interdependencies within the organization (Henderson & Cockburn, 1994; Siggelkow, 2002; March, 1991), above and beyond mere repetition and accumulated experience. Showing how the IPO can be a demarcation point for divergent innovation strategies calls for more research into this and other discrete windows of plasticity, which may help us understand better the origins of heterogeneity in strategy and performance.



## REFERENCES

- Ahuja, G. & Katila, R. (2001). Technological acquisitions and the innovation performance of acquiring firms: A longitudinal study. *Strategic Management Journal*, 22(3), 197–220.
- Ahuja, G. & Katila, R. (2004). Where do resources come from? The role of idiosyncratic situations. *Strategic Management Journal*, 25(8-9), 887–907.
- Albino-Pimentel, J., Dussauge, P., & Shaver, J. M. (2018). Firm non-market capabilities and the effect of supranational institutional safeguards on the location choice of international investments. *Strategic Management Journal*, 39(10), 2770–2793.
- Amburgey, T. L. & Miner, A. S. (1992). Strategic momentum: The effects of repetitive, positional, and contextual momentum on merger activity. *Strategic Management Journal*, 13(5), 335–348.
- Argote, L. (1999). Organizational Learning Curves: An Overview. In *Organizational Learning: Creating, Retaining, and Transferring Knowledge* (pp. 1–34).
- Arora, A., Belenzon, S., & Rios, L. (2014). Make, buy, organize: The interplay between research, external knowledge, and firm structure. *Strategic Management Journal*, 35(3), 317–337.
- Arrow, K. J. (1962). Economic welfare and the allocation of resources for invention. In *The Rate and Direction of Inventive Activity: Economic and Social Factors* (pp. 609–626). NBER.
- Arthur, W. B. (1996). Increasing returns and the new world of business. *Harvard Business Review*, (July-August), 100–109.
- Ball, E., Chiu, H. H., & Smith, R. (2011). Can VCs time the market? An analysis of exit choice for venture-backed firms. *The Review of Financial Studies*, 24(9), 3105–3138.
- Barkema, H. G. & Schijven, M. (2008). How do firms learn to make acquisitions? A review of past research and an agenda for the future. *Journal of Management*, 34(3), 594–634.
- Baum, J. A. & Amburgey, T. L. (2001). Organizational ecology. In *Companion to Organizations*, number 416 (pp. 304–326). Blackwell Publishing.
- Bernstein, S. (2015). Does going public affect innovation? *The Journal of Finance*, 70(4), 1365–1403.
- Bettis, R., Gambardella, A., Helfat, C. E., & Mitchell, W. (2014). Quantitative Empirical Analysis in Strategic Management. *Strategic Management Journal*, 35.
- Bingham, C. B., Eisenhardt, K. M., & Davis, J. P. (2007). Understanding What Firms Learn From Their Process Experience and How That Learning Unfolds Over Time. *Working Paper*, (617), 1–58.
- Boeker, W. (1989). Strategic change: The effects of founding and history. *Academy of Management Journal*, 32(3), 489–515.

- Bradley, S., Aldrich, H. E., Shepherd, D., & Wiklund, J. (2010). Resources, Environmental Change, and Survival: Asymmetric Paths of Young Independent and Subsidiary Organizations. *Strategic Management Journal*, (September 2008).
- Capron, L. & Mitchell, W. (2009). Selection capability: How capability gaps and internal social frictions affect internal and external strategic renewal. *Organization Science*, 20(2), 294–312.
- Carpenter, R. E. & Petersen, B. C. (2002). Is the growth of small firms constrained by internal finance? *The Review of Economics and Statistics*, 84(2), 298–309.
- Cassiman, B. & Veugelers, R. (2006). In Search of Complementarity in Innovation Strategy: Internal R&D and External Knowledge Acquisition. *Management Science*, 52(1), 68–82.
- Castrogiovanni, G. J. (1991). Environmental munificence : A theoretical assessment. *Academy of Management Review*, 16(3), 542–565.
- Celikyurt, U., Sevilir, M., & Shivdasani, A. (2010). Going public to acquire? The acquisition motive in IPOs. *Journal of Financial Economics*, 96(3), 345–363.
- Chang, S., Kogut, B., & Yang, J. (2016). Global Diversification Discount and its Discontents: A Bit of Self-Selection Makes a World of Difference. 37, 2254–2274.
- Chauvet, M. (1998). An Econometric Characterization of Business Cycle Dynamics with Factor Structure and Regime Switching. *International Economic Review*, 39(4).
- Clarysse, B., Bruneel, J., & Wright, M. (2011). Explaining growth paths of young technology-based firms: Structuring resource portfolios in different competitive environments. *Strategic Entrepreneurship Journal*, 5.
- Cockburn, I., Henderson, R. M., & Stern, S. (2000). Untangling the origins of competitive advantage. *Strategic Management Journal*, 21(10/11), 1123–1145.
- Cuyppers, I., Cuyppers, Y., & Martin, X. (2017). When the target may know better: Effects of experience and information asymmetries on value from mergers and acquisitions. *Strategic Management Journal*, 20(1).
- Cyert, R. M. & March, J. G. (1963). *A Behavioral Theory of the Firm*. Prentice Hall.
- Dalle, J.-M., Den Besten, M., & Menon, C. (2017). Using Crunchbase for economic and managerial research. *OECD Working Paper Series*.
- David, P. A. (1985). Clio and the economics of QWERTY. *The American Economic Review*, 75(2), 332–337.
- David, P. A. (1992). Heroes, herds and hysteresis in technological history: Thomas Edison and ‘The Battle of the Systems’ reconsidered. *Industrial and Corporate Change*, 1(1), 129–180.
- Dess, G. & Beard, D. W. (1984). Dimensions of Organizational Task Environments. *Administrative Science Quarterly*, 29(1).

- Dierickx, I. & Cool, K. O. (1989). Asset stock accumulation and sustainability of competitive advantage. *Management Science*, 35(12), 1504–1511.
- Dutta, S. (2016). Venture Capital Influence on Innovation: A Fund-Level Perspective. *Academy of Management Proceedings*, 2015(1), 18806–18806.
- Eisenhardt, K. M. & Schoonhoven, C. B. (1990). Organizational growth: Linking founding team, strategy, environment, and growth among US semiconductor ventures, 1978-1988. *Administrative Science Quarterly*, 35(3), 504–529.
- Färber, M., Menne, C., & Harth, A. (2018). A Linked Data wrapper for CrunchBase. *Semantic Web*, 9(4), 505–515.
- Fern, M. J., Cardinal, L. B., & O’Neill, H. M. (2012). The genesis of strategy in new ventures: Escaping the constraints of founder and team knowledge. *Strategic Management Journal*, 33(4), 427–447.
- Fox-Wolfgramm, S., Boal, K., & Hunt, J. (1998). Organizational adaptation to institutional change: A comparative study of first-order change in prospector and defender banks. *Administrative Science Quarterly*, 43(1), 87–126.
- Gans, J. S., Hsu, D. H., & Stern, S. (2008). The impact of uncertain intellectual property rights on the market for ideas: Evidence from patent grant delays. *Management Science*, 54(5).
- Gavetti, G. & Levinthal, D. A. (2004). 50th anniversary article: The strategy field from the perspective of management science: Divergent strands and possible integration. *Management Science*, 50(10), 1309–1318.
- Gavetti, G. & Rivkin, J. W. (2007). On the origin of strategy: Action and cognition over time. *Organization Science*, 18(3), 420–439.
- Golubov, A., Yawson, A., & Zhang, H. (2015). Extraordinary acquirers. *Journal of Financial Economics*, 116(2), 314–330.
- Gompers, P. A. (1996). Grandstanding in the venture capital industry. *Journal of Financial Economics*, 42(1), 133–156.
- Graebner, M. E. & Eisenhardt, K. M. (2004). The Seller’s Side of the Story: Acquisition as Courtship and Governance as Syndicate in Entrepreneurial Firms. *Administrative Science Quarterly*, 49(3), 366–403.
- Grimpe, C. & Hussinger, K. (2014). Resource complementarity and value capture in firm acquisitions: The role of intellectual property rights. *Strategic Management Journal*, 35.
- Haleblian, J., Devers, C. E., McNamara, G., Carpenter, M. A., & Davison, R. B. (2009). Taking stock of what we know about mergers and acquisitions: A review and research agenda. *Journal of Management*, 35(3), 469–502.
- Hall, B. H., Jaffe, A. B., & Trajtenberg, M. (2001). The NBER patent citations data file: Lessons, insights and methodological tools. *NBER Working Papers Series*.

- Hannan, M. T. & Freeman, J. (1977). The population ecology of organizations. *American Journal of Sociology*, 82(5), 929–964.
- Hannan, M. T. & Freeman, J. (1984). Structural inertia and organizational change. *American Sociological Review*, 49(2), 149–164.
- Harford, J. (2005). What drives merger waves? *Journal of Financial Economics*, 77(3), 529–560.
- Haspeslagh, P. C. & Jemison, D. B. (1991). *Managing acquisitions: Creating value through corporate renewal* (3 ed.). Free Press.
- Hayward, M. L. (2002). When do firms learn from their acquisition experience? Evidence from 1990 to 1995. *Strategic Management Journal*, 23(1), 21–39.
- Helfat, C. E. & Lieberman, M. B. (2002). The birth of capabilities: market entry and the importance of pre-history. *Industrial and Corporate Change*, 11(4), 725–760.
- Helfat, C. E. & Winter, S. G. (2011). Untangling dynamic and operational capabilities: Strategy for the (N)ever-changing world. *Strategic Management Journal*, 32(11), 1243–1250.
- Henderson, R. M. & Cockburn, I. (1994). Measuring competence? Exploring firm effects in pharmaceutical research. *Strategic Management Journal*, 15(S1), 63–84.
- Henderson, R. M. & Cockburn, I. (1996). Scale, scope, and spillovers: the determinants of research productivity in drug discovery. *The Rand journal of economics*, 27(1), 32–59.
- Higgins, M. J. & Rodriguez, D. (2006). The outsourcing of R&D through acquisitions in the pharmaceutical industry. *Journal of Financial Economics*, 80(2), 351–383.
- Hitt, M. A., Harrison, J. S., & Ireland, R. D. (2001). *Mergers & acquisitions: A guide to creating value for stakeholders*. Oxford University Press.
- Hsu, D. H. & Ziedonis, R. (2013). Resources as dual sources of advantage: Implications for valuing entrepreneurial-firm patents. *Strategic Management Journal*, 34(7), 761–781.
- Jemison, D. E. & Sitkin, S. B. (1986). Corporate acquisitions: A process perspective. *Academy of Management Review*, 11(1), 145–163.
- Kaplan, S. N. & Lerner, J. (2010). It ain't broke: The past, present, and future of venture capital. *Journal of Applied Corporate Finance*, 22(2), 36–47.
- Katz, R. & Allen, T. J. (1982). Investigating the Not Invented Here (NIH) syndrome: A look at the performance, tenure, and communication patterns of 50 R&D Project Groups. *R&D Management*, 12(1), 7–20.
- Kerr, W. R., Lerner, J., & Schoar, A. (2011). The consequences of entrepreneurial finance: Evidence from angel financings. *Review of Financial Studies*, 27(1), 20–55.
- Kimberly, J. R. (1975). Environmental constraints and organizational structure: A comparative analysis of rehabilitation organizations. *Administrative Science Quarterly*, 20(1), 1–9.

- Leonard-Barton, D. (1992). Core capabilities and core rigidities: A paradox in managing new product development. *Strategic Management Journal*, 13(1), 111–125.
- Levinthal, D. A. (2006). Imprinting and the evolution of firm capabilities. In *The SMS Blackwell Handbook of Organizational Capabilities* (pp. 100–103). Hoboken, NJ: Blackwell Publishing.
- Levinthal, D. A. & Marino, A. (2015). Three facets of organizational adaptation: selection, variety, and plasticity. *Organization Science*, 26(3), 743–755.
- Levitt, B. & March, J. G. (1988). Organizational learning. *Annual Review of Sociology*, 14, 319–340.
- Lippman, S. A. & Rumelt, R. (1982). Uncertain imitability: an analysis of interfirm differences in efficiency under competition. *The Bell Journal of Economics*, 13(2), 418–438.
- Lok, J. & De Rond, M. (2013). On the plasticity of institutions: Containing and restoring practice breakdowns at the Cambridge University Boat Club. *Academy of Management Journal*, 56(1).
- March, J. G. (1991). Exploration and exploitation in organizational learning. *Organization Science*, 2(1), 71–87.
- Mitchell, M. L. & Mulherin, J. H. (1996). The impact of industry shocks on takeover and restructuring activity. *Journal of Financial Economics*, 41(2), 193–229.
- Nelson, R. R. & Winter, S. G. (1982). *An evolutionary theory of economic change*. The Belknap Press of Harvard University Press.
- Newey, W. (1987). Efficient estimation of limited dependent variable models with endogenous explanatory variables. *Journal of Econometrics*, 36, 231–250.
- Puranam, P., Singh, H., & Chaudhuri, S. (2009). Integrating acquired capabilities: When structural integration is (un) necessary. *Organization Science*, 20(2), 313–328.
- Puranam, P., Singh, H., & Zollo, M. (2006). Organizing for innovation: Managing the coordination-autonomy dilemma in technology acquisitions. *Academy of Management Journal*, 49(2), 263–280.
- Puranam, P. & Srikanth, K. (2007). What they know vs. what they do: How acquirers leverage technology acquisitions. *Strategic Management Journal*, 28(8), 805–825.
- Ranft, A. L. & Lord, M. D. (2000). Acquiring new knowledge: The role of retaining human capital in acquisitions of high-tech firms. *The Journal of High Technology Management Research*, 11(2), 295–319.
- Ritter, J. R. & Welch, I. (2002). A review of IPO activity, pricing, and allocations. *The Journal of Finance*, 57(4), 1795–1828.
- Sears, J. & Hoetker, G. (2014). Technological overlap, technological capabilities, and resource recombination in technological acquisitions. *Strategic Management Journal*, 35(1), 48–67.

- Semadeni, M., Withers, M. C., & Trevis Certo, S. (2014). The perils of endogeneity and instrumental variables in strategy research: Understanding through simulations. *Strategic Management Journal*, 35(7), 1070–1079.
- Shleifer, A. & Vishny, R. W. (2003). Stock market driven acquisitions. *Journal of Financial Economics*, 70(3), 295–311.
- Siggelkow, N. (2002). Evolution toward fit. *Administrative Science Quarterly*, 47(1), 125–159.
- Siggelkow, N. (2011a). Firms as systems of interdependent choices. *Journal of Management Studies*, 48(5), 1126–1140.
- Siggelkow, N. (2011b). Firms as systems of interdependent choices. *Journal of Management Studies*, 48(5), 1126–1140.
- Staw, B. M. & Szwajkowski, E. (1975). The Scarcity-Munificence Component of Organizational Environments and The Commission of Illegal Acts. *Administrative Science Quarterly*, 20(3), 345–354.
- Stern, S. (2004). Do scientists pay to be scientists? *Management Science*, 50(6), 835–853.
- Stinchcombe, A. L. (1965). Social structure and organizations. In J. G. March (Ed.), *Handbook of Organizations (RLE: Organizations)*, volume 20 chapter 4, (pp. 142–193). Taylor & Francis, Abingdon UK.
- Stuart, T. E. & Sorenson, O. (2003). Liquidity events and the geographic distribution of entrepreneurial activity. *Administrative Science Quarterly*, 48(2), 175–201.
- Szulanski, G. (2009). Exploring internal stickiness: Impediments to the transfer of best practices within the firm. *Strategic Management Journal*, 17, 27–43.
- Thompson, J. D. (1967). *Organizations in action: Social science bases of administrative theory* (reprint, r ed.). Transaction Publishers.
- Trichternborn, A., Knyphausen-Augfseß, D., & Schweizer, L. (2016). How to improve acquisition performance: The role of a dedicated M&A function, M&A learning process, and M&A Capability. *Strategic Management Journal*, (37).
- Tripsas, M. & Gavetti, G. (2000). Capabilities, cognition, and inertia: Evidence from digital imaging. *Strategic Management Journal*, 21(10-11), 1147–1161.
- Vergne, J. & Durand, R. (2010). The missing link between the theory and empirics of path dependence: conceptual clarification, testability issue, and methodological implications. *Journal of Management Studies*, 47(4), 736–759.
- von Hippel, E. (1994). "Sticky Information" and the Locus of Problem Solving: Implications for Innovation. *Management Science*, 40(4), 429–439.
- VonEije, J. H., DeWitte, M. C., & VanderZwaan, A. H. (2013). IPO-related organizational change and long-term performance: considerations of Dutch corporate officers. *Managerial Finance*, 30(1), 17–28.

- Weick, K. E., Sutcliffe, K. M., & Obstfeld, D. (2005). Organizing and the Process of Sensemaking. *Organization Science*, 16(4), 409–421.
- Williamson, O. E. (1975). *Markets and Hierarchies: Analysis and Antitrust Implications*. New York: Free Press.
- Wooldridge, J. M. (2010). *Econometric Analysis of Cross Section and Panel Data*. MIT press Cambridge, MA.
- Zollo, M. & Meier, D. (2008). What is M&A performance? *The Academy of Management Perspectives*, 22(3), 55–77.
- Zollo, M. & Singh, H. (2004). Deliberate learning in corporate acquisitions: post-acquisition strategies and integration capability in U.S. bank mergers. *Strategic Management Journal*, 25(13), 1233–1256.
- Zollo, M. & Winter, S. G. (2002). Deliberate learning and the evolution of dynamic capabilities. *Organization Science*, 13(3), 339–351.

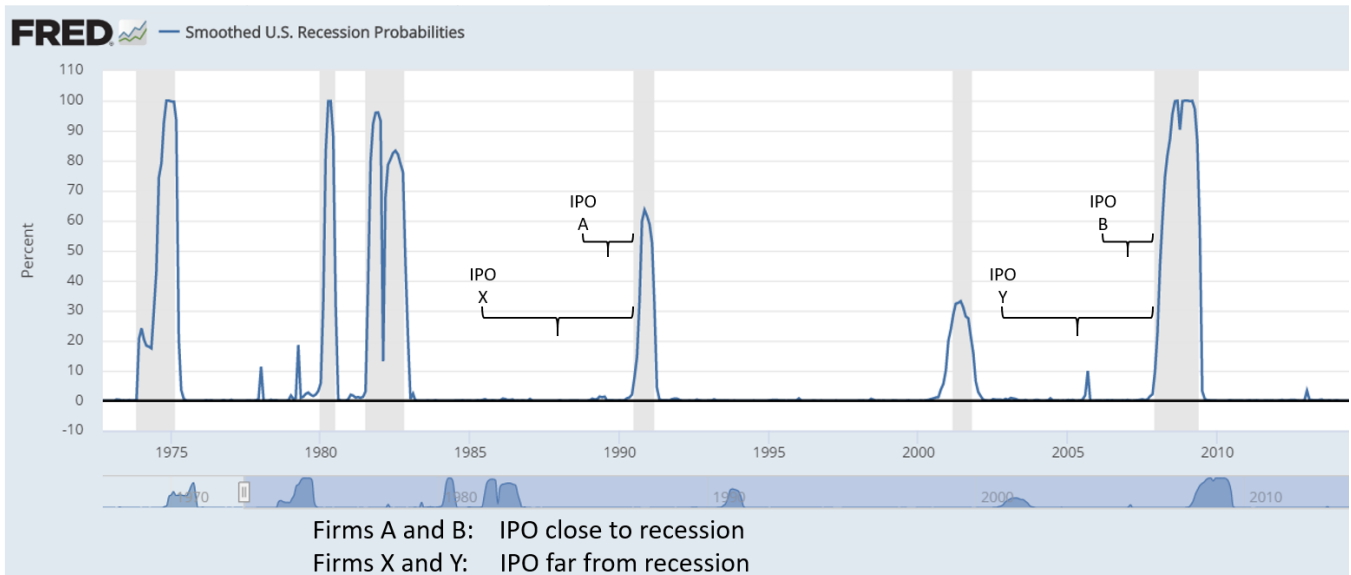


Figure 1: Visualization of main explanatory variable: For each sample firm, *Months\_post* is the number of months between IPO and beginning of next recession (shown by labels and brackets superimposed on chart). Source image from St. Louis Fed, modeled after Piger and Chauvet, *Smoothed U.S. Recession Probabilities* (1998). Retrieved from <https://fred.stlouisfed.org/series>.

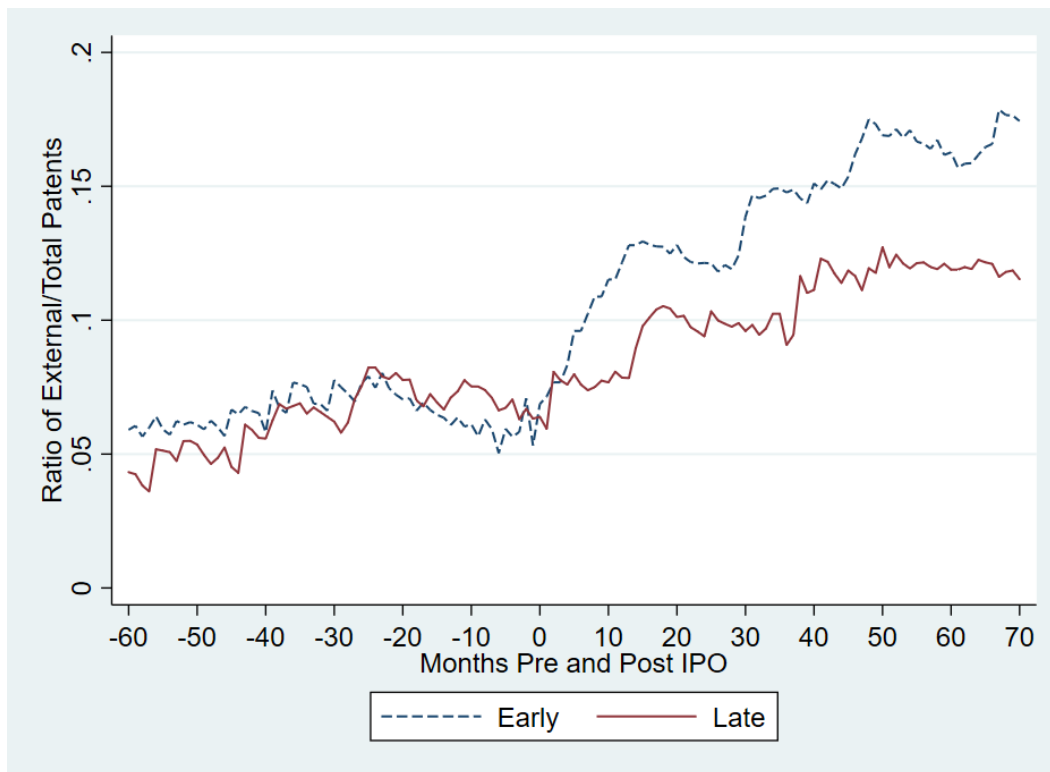


Figure 2: Share of external patents held by firms. Firms were coded as *Early* or *Late* depending on whether their IPO occurred before or after the midpoint between recessions. We can see that all firms increase their acquisition of external patents after IPO, but early firms do so more sharply.



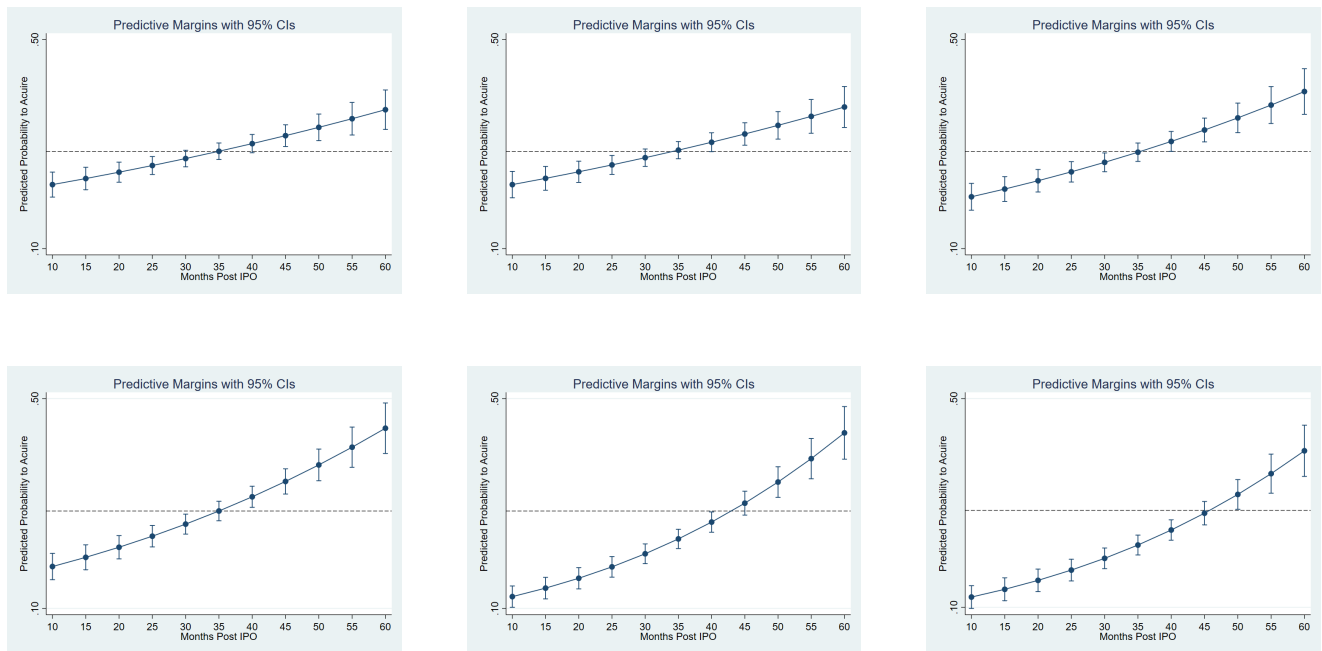


Figure 3: Predicted Probabilities for Probit regressions (Table 4) at 5, 8, 11, 14, 17, and 20 years post IPO

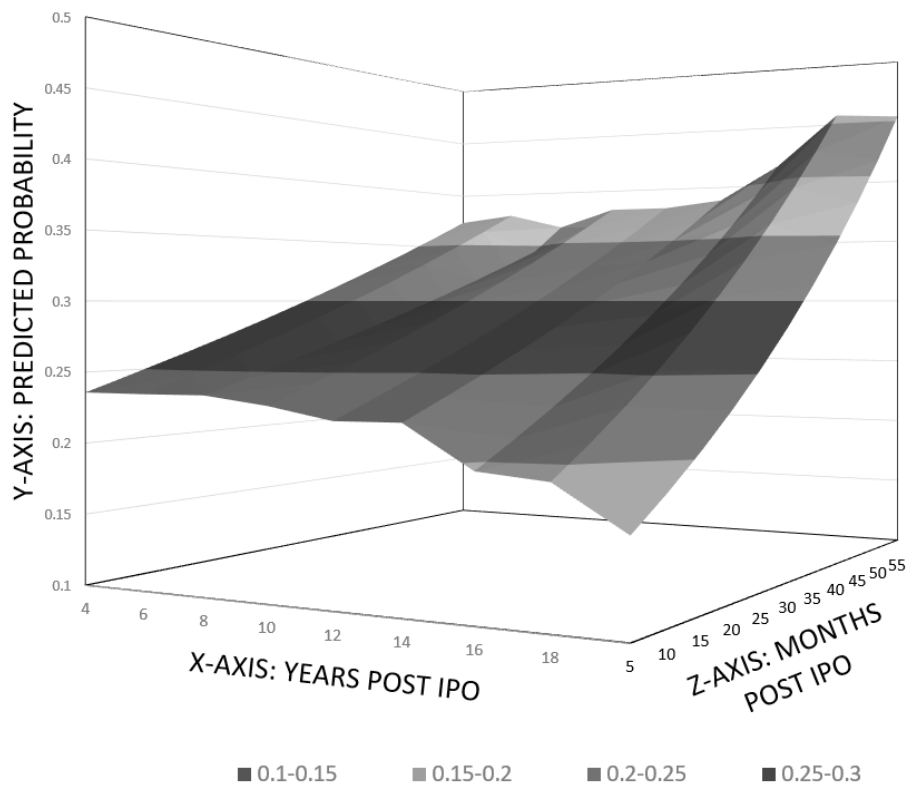


Figure 4: Surface plot of 10 separate predicted probability plots for years 4-20.

Table 1: Descriptive Statistics and Bivariate Correlation matrix

	Mean	SD	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) Tech_Acq	0.272	0.26	1.00										
(2) Months Post-IPO	33.18	32.47	0.01 (0.045)	1.00									
(3) Vintage Year	5.53	2.88	0.01 (0.333)	-0.102 (0.007)	1.00								
(4) Employees	4.47	22.07	0.02 (0.000)	-0.02 (0.032)	0.00 (0.551)	1.00							
(5) Age Observed	13.26	5.70	0.01 (0.022)	0.06 (0.180)	-0.00 (0.393)	-0.05 (0.000)	1.00						
(6) Age.at.IPO	8.63	6.88	-0.01 (0.018)	0.01 (0.312)	-0.00 (0.890)	0.12 (0.000)	0.01 (0.346)	1.00					
(7) Assets	1479	9763	0.03 (0.000)	-0.03 (0.153)	-0.00 (0.978)	0.58 (0.000)	-0.01 (0.124)	0.12 (0.000)	1.00				
(8) Patent Stock	374.62	1806	0.09 (0.000)	-0.00 (0.612)	0.01 (0.296)	0.12 (0.000)	-0.02 (0.005)	0.06 (0.000)	0.20 (0.000)	1.00			
(9) R&D Expense	53.79	323.75	0.07 (0.000)	-0.07 (0.000)	0.01 (0.386)	0.27 (0.000)	-0.03 (0.000)	0.15 (0.000)	0.46 (0.000)	0.57 (0.000)	1.00		
(10) Sales	1135	77294	0.03 (0.000)	-0.03 (0.271)	-0.00 (0.657)	0.69 (0.000)	-0.03 (0.000)	0.12 (0.000)	0.77 (0.000)	0.16 (0.000)	0.34 (0.000)	1.00	
(11) Year	1999	8.24	0.02 (0.001)	-0.10 (0.000)	-0.00 (0.449)	0.07 (0.000)	-0.00 (0.619)	0.58 (0.000)	0.12 (0.000)	0.01 (0.278)	0.12 (0.000)	0.11 (0.000)	1.00
Observations	14105												

Table 2: Yearly Cross-sectional Regressions Observed at Various Years Post-IPO

Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Years Post-IPO:	3	5	7	9	11	13	15	17	19	21
DV: Tech_Acquisitions										
<i>Months_pre</i>	0.0090 (0.002)	0.0102 (0.002)	0.0105 (0.003)	0.0111 (0.008)	0.0107 (0.014)	0.0099 (0.026)	0.0083 (0.013)	0.0097 (0.018)	0.0087 (0.029)	0.0104 (0.052)
<i>ln(Employees)</i>	-0.1096 (0.036)	-0.0961 (0.065)	-0.0989 (0.063)	-0.0681 (0.214)	0.0049 (0.929)	0.0664 (0.251)	0.0582 (0.350)	0.0901 (0.167)	0.1468 (0.032)	0.1291 (0.079)
<i>Age</i>	0.0018 (0.694)	0.0004 (0.939)	-0.0018 (0.722)	0.0027 (0.593)	-0.0027 (0.623)	-0.0028 (0.622)	0.0027 (0.654)	0.0057 (0.370)	0.0113 (0.096)	0.0172 (0.017)
<i>Age.at_IPO</i>	-0.0181 (0.323)	0.0092 (0.622)	0.0108 (0.578)	-0.0164 (0.414)	-0.0363 (0.083)	-0.0655 (0.003)	-0.0693 (0.004)	-0.0624 (0.015)	-0.0626 (0.021)	-0.0381 (0.189)
<i>ln(Assets)</i>	0.1584 (0.000)	0.1464 (0.000)	0.1543 (0.000)	0.1518 (0.000)	0.1203 (0.000)	0.0944 (0.002)	0.1076 (0.002)	0.0704 (0.052)	0.146 (0.007)	0.0189 (0.006)
<i>ln(Patent.stock)</i>	0.0785 (0.000)	0.0639 (0.000)	0.0489 (0.006)	0.0473 (0.012)	0.0584 (0.003)	0.0523 (0.013)	0.0688 (0.003)	0.0919 (0.000)	0.1031 (0.000)	0.1009 (0.000)
<i>ln(R&amp;D_exp)</i>	-0.0661 (0.002)	-0.0577 (0.009)	-0.0434 (0.054)	-0.0416 (0.069)	-0.0408 (0.078)	-0.0469 (0.047)	-0.0483 (0.048)	-0.0399 (0.120)	-0.0313 (0.255)	-0.0275 (0.352)
<i>ln(Sales)</i>	0.0251 (0.797)	-0.0295 (0.768)	0.0808 (0.436)	0.1849 (0.087)	0.2697 (0.019)	0.1031 (0.398)	0.1437 (0.288)	0.0930 (0.511)	-0.2287 (0.133)	-0.2030 (0.209)
<i>Constant</i>	-2.3230	-2.1425	-2.1321	-2.1062	-1.7935	-1.7146	-2.1382	-2.2599	-1.9428	-2.3591
Observations	1201	1098	977	913	812	801	697	574	446	367
Pseudo R <sup>2</sup>	0.184	0.180	0.191	0.178	0.145	0.1345	0.125	0.124	0.118	0.109
Pre-IPO Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Cross sectional probit regressions at various years post-IPO. Unit of observation is the firm. Dependent variable is a dummy for whether firm engaged in at least one technological acquisition that year. *p*-values in parentheses. Standard errors clustered at the firm level and robust to arbitrary heteroskedasticity.

Table 3: Effect of controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Tech_Acq	Tech_Acq	Tech_Acq	Tech_Acq	Tech_Acq	Tech_Acq	Tech_Acq	Tech_Acq
Tech_Acq								
Months_pre	0.0094 (0.000)	0.0087 (0.054)	0.0082 (0.056)	0.0082 (0.039)	0.0103 (0.031)	0.0107 (0.029)	0.0112 (0.012)	0.0109 (0.013)
ln(Employees)		0.1792 (0.000)	0.1794 (0.000)	0.2149 (0.000)	-0.0013 (0.960)	0.0004 (0.988)	-0.0099 (0.707)	-0.0381 (0.176)
Age			0.0015 (0.564)	0.0015 (0.560)	-0.0005 (0.859)	0.0003 (0.895)	-0.0001 (0.959)	-0.0012 (0.665)
Age.at_IPO				-0.0200 (0.000)	-0.0228 (0.000)	-0.0234 (0.000)	-0.0230 (0.000)	-0.0236 (0.000)
ln(Assets)					0.1290 (0.000)	0.1024 (0.000)	0.1159 (0.000)	0.1282 (0.000)
ln(Patents)						0.0473 (0.000)	0.0604 (0.000)	0.0624 (0.000)
ln(R&D_exp)							-0.0365 (0.125)	-0.0339 (0.129)
ln(Sales)								0.1633 (0.003)
Constant	-2.0777	-2.0649	-2.0737	-1.9605	-2.3680	-2.4072	-2.2241	-2.0755
Observations	846	846	846	846	846	846	846	846
Pseudo R <sup>2</sup>	0.0323	0.0411	0.0670	0.0741	0.141	0.147	0.159	0.167
Pre-IPO Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Cross sectional probit regressions at 10 years post-IPO. Unit of observation is the firm. Dependent variable is a dummy for whether firm engaged in at least one technological acquisition that year. *p*-values in parentheses. Standard errors clustered at the firm level and robust to arbitrary heteroskedasticity.

Table 4: Robustness Tests: Fund Vintage as Instrument for IPO Timing

Model:	(1)	(2)	(3)	(4)	(5)
Dependent variable:	Tech_Acq	Tech_Acq	Tech_Acq	Months_pre	Tech_Acq
Estimation:	Probit	IV	IV	OLS 1st Stg	OLS
STATA function:	probit	eprobit	ivprobit	regress	regress
Months_pre	0.00887 (0.032)	0.00720 (0.047)	0.00831 (0.041)		
Vintage Year (IV)				-2.375 (0.002)	0.0010 (0.212)
ln(Employees)	-0.0078 (0.807)	-0.0006 (0.790)	-0.1136 (0.000)	0.0700 (0.888)	0.0072 (0.123)
Firm Age	0.0013 (0.670)	0.0001 (0.669)	-0.0131 (0.000)	0.3844 (0.000)	0.0005 (0.232)
Age_at_IPO	-0.0263 (0.000)	-0.0018 (0.000)	-0.0387 (0.000)	2.2232 (0.000)	-0.0003 (0.622)
ln(Assets)	0.1152 (0.000)	0.0078 (0.000)	0.0506 (0.148)	0.0760 (0.012)	0.0139 (0.000)
ln(Patent_stock)	0.0673 (0.000)	0.0045 (0.000)	0.0169 (0.427)	-0.4315 (0.007)	0.0102 (0.000)
ln(R&D_exp)	-0.0460 (0.000)	-0.0031 (0.003)	0.0204 (0.240)	-0.0431 (0.028)	-0.0055 (0.005)
ln(Sales)	0.0907 (0.151)	0.0061 (0.166)	0.1806 (0.000)	-0.2162 (0.143)	0.0011 (0.887)
Constant	-2.2657	-2.3469	-2.6053	15.1605	-0.1508
Observations	451	451	451	451	451
$R^2$				0.2246	0.133
Chi <sup>2</sup>	513	258	221		
Pseudo $R^2$	0.101				
F-statistic	22.14	(0.0008)	17.69	17.17	28.04
Pre-IPO Characteristics	Yes	Yes	Yes	Yes	Yes
Year Controls	Yes	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes	Yes

Cross sectional regressions at 10 years post-IPO. Unit of observation is the firm. Dependent variable on models 1,2, 3, 5 is a dummy for whether firm engaged in at least one technological acquisition that year. Model 4 shows the conditional correlation between *IPO timing* and *Vintage Year* (the Instrumental Variable in models 2 and 3). *p*-values in parentheses. Standard errors clustered at the firm level and robust to arbitrary heteroskedasticity.