A Date with Destiny: How the Post-IPO Environment Shapes Long-run innovation strategy[†]

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Abstract

Using novel data on 1,265 newly-public firms, I show that innovative firms exposed to environments with lower M&A activity just after their initial public offering (IPO) adapt by engaging in fewer technological acquisitions and more internal research. However, this adaptive response becomes inertial shortly after IPO and persists well into maturity. This study advances our understanding of how the environment shapes heterogeneity and capabilities through its impact on firm structure. I discuss how my results can help bridge inertial versus adaptive perspectives in the study of organizations, by documenting an instance when the two interact.

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1. Introduction

How does an organization's unique past shape its future? This paper contributes to our understanding of the origins of heterogeneity and capabilities by showing how the post-IPO environment influenced the divergent evolution of 1,265 technology firms, towards either a more internal or external innovation strategy. A key assumption in modern strategy is that firm differences are important precisely because they at once enable and constrain capabilities (Penrose, 1959). But we know little about how differences originate, evolve, and persist (Cockburn et al., 2000; Siggelkow, 2011). Within the study of innovation in particular, we know that technology firms often draw on both internal and external sources for critical inputs (Cohen and Levinthal, 1990; Kogut and Zander, 1992), but why they favor one channel versus the other is unclear (Arora et al., 2014; Pisano, 1990). My paper proposes one mechanism that may explain some of this divergence: Firms lack fully-developed capabilities for either internal or external technology sourcing at the time of going public, and begin growing through whichever method is most efficient given the prevailing environment. This temporary response then persists because IPOs involve intense firm-level transformation and high plasticity (Gavetti and Rivkin, 2007; Stuart and Sorenson, 2003), leading to structural changes which are then hard to change (Stinchcombe, 1965).

I test this hypothesis using a novel dataset which details the ownership, financial, acquisition, and patenting history for all technology firms that went public between 1975 and 2008. I exploit a series of cyclical shocks that create unfavorable environments for technology acquisition. For firm s that go public late within a cycle, the shocks occur closer to their IPO–a period when firms undergo a rapid expansion of their technological portfolios. This raises search and transaction costs for external technology at a time when firms normally seek growth via acquisitions (Bernstein, 2014; Celikyurt and Sevilir, 2010). I argue that this reduces late firms acquisition opportunities in the short run. And if this results in under-developed acquisition capabilities, we should see this reflected in their long-run innovation strategy. Conversely, because firms still need to find sources of growth, decreased acquisition opportunities should increase their effort, investment and capabilities related to internal research.

While prior work has identified early conditions in a firm's history as key determinants of heterogeneity in capabilities (Boeker, 1989; Eisenhardt and Schoonhoven, 1990; Holbrook et al., 2000), we still lack a coherent theory on how and when firms are constrained by the past. For example, there is evidence that firms cannot adapt after radically changed institutional environments (Kogut and Zander, 2000), but on the other hand, firms often change after the original founder leaves (Hannan et al., 1996). Similarly, while early work suggested that the link between founding and persistence operates through cognitive mechanisms (Boeker, 1989), more recent scholars argue that it is likely to involve multi-level interactions (Marquis, 2013; Siggelkow, 2011), or may operate through limiting the set of local optimization options (Levinthal, 1997). Just as importantly, the literature is virtually silent on which of these mechanisms are responsive to managerial intervention. Therefore, in this paper I look at just one specific temporal setting (the post-IPO window) and one possible conditioning factor (the economic environment), in order to focus the discussion and hopefully clarify and extend prior findings of this diverse literature.

Specifically, I focus on patenting firms exposed to depressed economic conditions after IPO. Market downturns cause temporary shift in the relative cost of internal development vs. acquisition of external technology (Stiglitz, 2000), which I argue will result in fewer opportunities to engage in M&A and more incentives to invest in internal research. Innovative firms are also sensitive to inertial forces, which should make these early decisions hard to change later. This is because innovation is characterized by lags between inputs and outputs, uncertainty, and imperfect appropriability (Arrow, 1962b; Cohen et al., 2000). Therefore we should expect to find enduring differences in the firms' future corporate strategy mix of business development (external acquisition) vs. internal development through organic R&D.

While this is a straightforward and intuitive argument, its empirical study faces an endogeneity problem. After all, firms pick the exact date of their IPO, thus choosing the economic environment in which they go public (Ritter and Welch, 2002). For example most firms go public during IPO waves, when the financial markets are robust, yet other firms chose (presumably rationally) to go public during recessionary periods. In either case, this self selection makes it difficult to identify the role played by the post-IPO environment on future firm characteristics.

To circumvent this problem, I employ a quasi-experimental setting which exploits the unpredictability in the length of corporate event waves (Harford, 2005). Instead of looking at the date of IPO itself as the independent variable, I focus on economic conditions *just after*, which only become revealed after the firm has made the decision to execute the IPO. I restrict the sample to firms that went public during active IPO waves that ended suddenly (there are seven such waves between 1975 and 2012). Then I assign firms to treatment and control groups based on the temporal distance between their IPO and the end of the wave. Since wave length varies from nine months to 3.5 years, firms cannot know *ex ante* if they are going public close to the end of a wave. Thus, while firms self-select to go public during an active period, they do not know if they will enjoy a long or short period of robust economic activity as newly-minted public firms. My results show stark differences in early (late) firms' reliance on technological acquisitions versus internal research. Firms exposed to fewer acquisition opportunities just after an IPO show 30% less acquisition intensity, even 25 years later. This is strong evidence of long-run persistence.

As expected, late firms also demonstrate higher levels of internal research, as reflected by patent-level measures like generality and originality. This is consistent with the view that the mechanism at work may involve the adaptation of firms' whole set of activities. In other words, acquisition experience does not simply increase acquisition capabilities, but also seems to reduce substitute activities. I also find differences in top management teams. Late firms have more science PhDs and fewer MBAs, which is consistent with more internal research and less acquisition activity.

Interestingly, I find little difference in terms of financial performance between firms that IPO closer or further away from the end of a wave, suggesting that firms adapt quickly given their initial post-IPO environments. However, I document stark performance and survival decreases for firms that do not fit within their *expected* strategy–for example highly acquisitive treated firms (i.e., that faced slow acquisition periods post IPO). This is an interesting finding, which calls for further study in order to better establish the direction of causality.

Taken together, my findings partly reconcile some of the tension between adaptation and selection (Hannan and Freeman, 1977; Levinthal, 1997), suggesting a brief period of adaptation after IPO followed by long-run inertia.[1] The effects documented show no signs of attenuation over time, even 25 years later.

The paper proceeds as follows: *Section 2* locates this study in relation to prior work on internal and external technology, founding and imprinting effects, and reconciling adaptation versus inertia; *Section 3* describes the empirical methodology, and why the

[1]In *Section 2* I discuss how my findings relate to and contrast with similar reconciliatory theories, such as punctuated equilibrium and adaptive search.

IPO setting is ideal for this study; *Section 4* describes the data, empirical tests, and results; *Section 5* discusses the implications for the study of innovation and organizations, as well as for managers; *Section 6* concludes by summarizing the results.

2. Theory and background

The inertial nature of technology sourcing

Most firms are unable to efficiently generate all the technology they need (Arrow, 1962a), and therefore complement internal research with externally sourced technology (Arora and Gambardella, 1994; Granstrand and Sjölander, 1990). In this section, I focus on the inertial nature of these activities, and highlight that both *make* and *buy* should require tacit organizational know-how developed over time. In other words, it is unlikely that firms can quickly become good at either activity.

With regards to *make*, it is well accepted that a firm's ability to perform internal research is closely related to other firm activities, takes time to accumulate, and that once mastered, it can provide competitive advantage (Cohen and Levinthal, 1990; Henderson and Cockburn, 1994). With regards to *buy*, however, the issue is not as obvious. While buying is sometimes characterized as a faster or more nimble way of acquiring resources (Higgins and Rodriguez, 2006; Karim and Mitchell, 2000; Puranam et al., 2006), successful buying and integration are also notoriously tacit and hard to master, learn-by-doing processes (Haleblian, 1999; Haspeslagh and Jemison, 1991). Thus, there is also a widely-held view that acquisitions either do not create value (Hitt and Hoskisson, 1996), or only do so given very specific contingencies (Ahuja and Katila, 2001).

A recurring problem in studying acquisitions comes from the fact that some firms buy often and are good at it, while others simply pursue different channels for accessing new resources (Graebner et al., 2010; Laamanen and Keil, 2008). Thus, I argue that *the ability to acquire itself* should also be heterogeneous, cumulative and path-dependent. These *buy* capabilities reside at the organizational level, accumulate over time, and interact recursively with *make* capabilities to perform internal research (Cohen and Levinthal, 1990). For example, as noted in detailed studies of Lycos and Vanguard, these firms became good at acquiring after a period of trial-and-error (Gavetti and Rivkin, 2007; Siggelkow, 2002), which involved several organizational readjustments. Summarizing the foregoing discussion, *buy* is somewhat of a paradox in that it is an activity that allows the firm to adapt, while the *ability* to buy well is subject to its own inertial pressures. As David Lawee, Google's Director of Acquisitions, put it:

> *"Integration is a really well-honed process now, I certainly wouldn't have said that four years ago. Four years ago we could get away with, You are smart, figure it out, because it was a smaller business"*[2]

This raises an interesting question, which motivates the present study: if technological *buy* capabilities must be learned, and in this regard are similar to *make* capabilities, what happens to firms that have fewer opportunities to buy during key formative stages? I propose that post-IPO firms have not yet developed either type of capability fully, and will begin growing via whichever method is most efficient given the prevailing environment. But since *make* and *buy* are at least partial substitutes (Arora et al., 2014), increasing reliance on one channel should result in decreasing reliance on the other. In other words, once a firm begins on a path to acquire often, it will not only get good at external sourcing, but it may also under-develop internal research capabilities. Thus, their initial vertical integration choices as public firms (with new resources and pressures) would be strongly conditioned by the environment, based on the prevailing

[2] http://www.xconomy.com/san-francisco/2012/03/05/googles-rules-of-acquisition-how-to-be-an-android-not-an-aardvark/

market and technological considerations (Gans et al., 2002; Pisano, 1990).

These early choices should result in the persistent favoring of one or another set of capabilities through the path-dependency of technology and accumulation of capabilities, routines and structures (Nelson and Winter, 1982; Siggelkow, 2011). This in turn should make future choices less conditioned by the environment and more conditioned by accumulated experience and abilities. In other words, their early environment might arbitrarily determine a firm's future reliance on a *make* or *buy* mode of growth, and lead to heterogeneous strategies at the population level.

Consistent with this view, many well-known firms such as Cisco Systems, Illinois Toolworks, Google, and Johnson & Johnson persistently gravitate towards the external channel. On the other hand, firms like Apple and IBM engage in considerably fewer acquisitions relative to their internal research efforts. Recent work has provided large-scale evidence that in fact most firms heavily favor either internal or external technology, and that a firm's orientation in this regard is highly persistent and related to organizational structure (Arora et al., 2014). While this earlier work does not establish causality, it strongly supports the view that firm-specific heterogeneity is related to the mutually reinforcing patterns of internal and external innovative activity.

The present paper helps us understand one source of divergence with regards to favoring an internal or external innovation strategy. As I more fully describe in the empirical section, I compare young, newly public firms faced with better (worse) opportunities to grow by acquisition just after their IPO. Then I observe them for several years and measure whether these initial conditions increased (decreased) the frequency of future *buy* decisions.

Origins of inertia: founding conditions and imprinting effects

At a more general level, there are many views on how events from the past influence a firm's present structure and conduct. Much of this work fits loosely under the umbrella of the *founding/founder effects* or *imprinting* literatures. For example, at the firm level, jobs and occupations, capabilities, and routines may reflect the conditions that were prevalent at their creation (Beckman and Burton, 2008). Similarly, at the individual level, workers' early and prior experiences both enable and constrain the range of their choices in the long run, even after changes in employment (Azoulay et al., 2009).[3]

My study differs from prior *imprinting/founding* work in an important way, by looking at a critical period that occurs years after founding: the months just after an IPO. This setting lets me explore the interplay between adaptation and inertia during an interesting window when the firm is on the cusp of maturity, but also still changing. An important difference between an IPO and a founding setting is that the survival rate for firms post IPO is staggering relative to that for new ventures. For example, studies by the Federal Reserve of New York find that 80% (Peristiani and Hong, 2004) of IPOs make it past their 7th anniversary, while the literature on entrepreneurship has documented survival rates of about 40% for new ventures (Headd, 2003; Phillips and Kirchhoff, 1989). This means that firms going public are less sensitive to population ecology mechanisms (e.g., liability of newness, resource constraints) that are often associated with imprinting theories (Stinchcombe, 1965).

A second difference is that IPO firms are likely to have developed a "life of their own" (Nelson, 1991), simply through their increased size and complexity, and thus be less of an embodiment of the entrepreneur.[4]

[3]See (Marquis, 2013) for a thorough review of the literature.

[4]For example, Carroll (1993) incisively remarks on theories of entrepreneurship: "While it is too strong to say that the entrepreneur is the organization, it is fair to say that this characterization depicts the organization as the social embodiment of his or her personality."

In sum, the setting allows us to better isolate a link between the economic environment and the evolution of the firm, just after crossing a major survival milestone and at a distance from the founder's original "blueprints" (Hannan et al., 1996).

Prior work reconciling adaptation and inertia

A number of approaches have sought to reconcile adaptive and inertial perspectives (Levinthal, 1991). Some have argued for a punctuated equilibrium model (PE), where firms sequentially alternate between periods of long-range inertia and quick, radical change (Miller and Friesen, 1982; Romanelli and Tushman, 1986). In this view, the catalysts for change may be under-performance or technological change.

In this study, I contribute to this literature by providing some of the clearest evidence to date of the sequential interaction between inertial and adaptive mechanisms. Clearly there are similarities between my study and the predictions of PE models, insofar as both involve short periods of rapid change. However, I emphasize that there are also important differences, since the IPO window is still relatively early in a firm's life (PE models assume maturity before change), and IPOs are brought about in response to high-performance, not risk of failure.

Another major bridge between adaptation and change posits that firms can adapt, but only within a narrow set of choices determined by initial conditions (Levinthal, 1997), and that innovation (as a form of problem solving) should similarly be constrained by interdepenencies (Fleming and Sorenson, 2001). An important contribution of this work is the development of models which explain the existence of firm heterogeneity even within the same market niche, as a result of different initial conditions. My study is closely related to this work, as I seek to find a link between early conditions, adaptation, and persistent heterogeneity. As I detail in the next sections, I contribute to this stream by providing empirical evidence to complement what has hitherto been primarily explored via computer simulations.

3. Empirical methodology

Recent work has shown that going public shifts firms' mix of channels for acquiring technology in an outward direction, replacing some of their original internal research with technology acquired through the purchase of other firms (Bernstein, 2014).

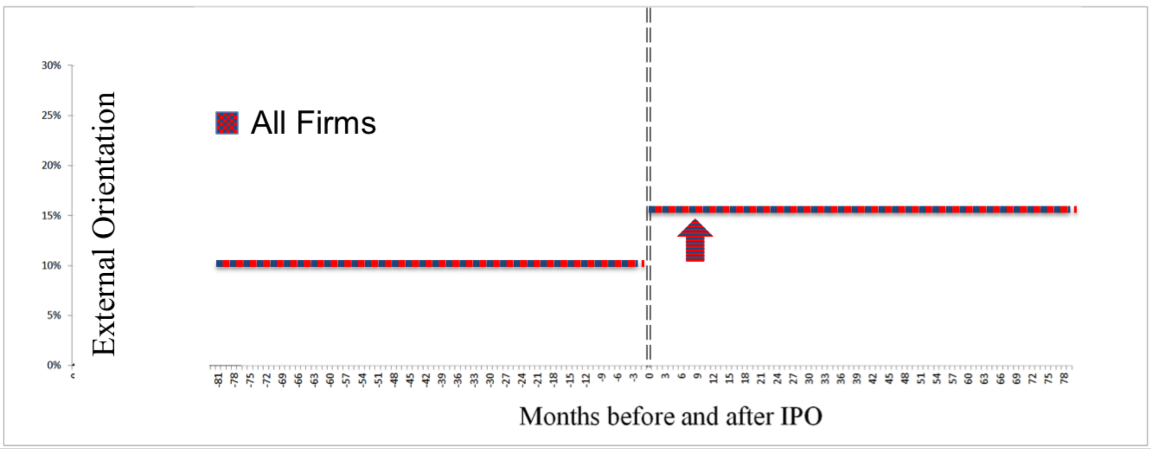

Figure 1: This figure shows a stylized depiction of the shift in technological orientation documented by Bernstein (2014).

In this paper I argue that the magnitude of this shift might not be uniformly distributed among all firms, but rather could be moderated by market frictions which interfere with firms' ability to purchase targets at the time that this re-orientation is occurring.

Specifically, my quasi-experiment tests whether going public in the later half of an IPO cycle causes firms to engage in fewer technological acquisitions (Ahuja and Katila, 2004) and more original research, even many years later. In this section I discuss: a) The identification strategy, and how I am able to characterize two discrete types of economic environments (favorable/unfavorable for technological acquisitions); b) the logic behind the empirical setting (the post-IPO period); c) Why technology firms should be highly adaptive during this window, but inertial afterwards.

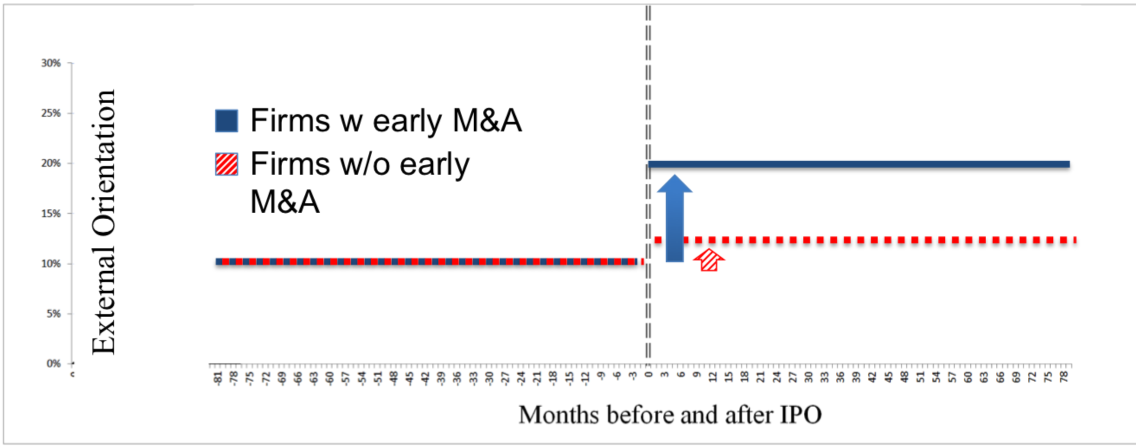

Figure 2: This figure shows a stylized depiction of the predicted differential shift in technological orientation: If firms late to the cycle have fewer options to acquire, they may compensate by investing in internal R%D, leading them down a different trajectory.

Identification strategy

I classify firms as *early* or *late*, depending on whether they go public on the first or second half of an IPO wave. I then test for the impact of environmental conditions that make it less efficient/desirable to access external technologies. I exploit two regularities that have been well-documented in the finance literature. First, IPOs come in waves which begin and end suddenly and unpredictably (Ritter and Welch, 2002). Second, the end of an IPO wave invariably comes due to a macroeconomic shock that also brings about conditions unfavorable for acquisitions (Mitchell and Mulherin, 1996).[5] Thus, building on much work in the economics of information, I argue that periods of slow economic activity should result in increased search costs for firms seeking technological assets in the market for firms Arrow (1974); Stigler (1961).

While it is beyond the scope of this paper to weigh competing explanations for such persistent correlations, it is safe to make two assertions: First, there is no reason to

[5]See also Stiglitz (2000) for a discussion of how fluctuations in financial markets affect investment decisions, especially for R&D intensive firms

believe that firms can reliably predict the end an IPO wave or an M&A at the time of going public, since waves come to an end due to macroeconomic shocks. Second, and most important: for all the periods under observation, IPO activity (the criteria used to assign treatment and control groups) and acquisition activity (the mechanism I argue should drive the divergence), both essentially shut down at the same time. *Figure 1* plots the 1999-2000 wave, showing that IPO activity and volume of small technological acquisitions are highly co-temporal.

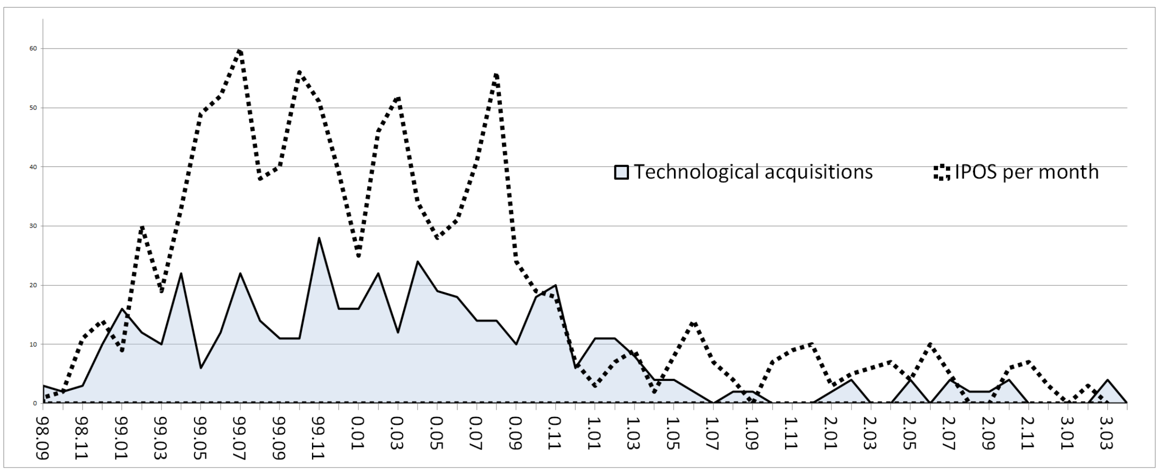

Figure 3: This figure illustrates the high degree of correlation between IPO waves and intensity of technological acquisitions, as observed during the 1999-2000 wave. Importantly, both IPO and acquisitions end sharply and almost at the same time. The horizontal axis shows months, and the vertical axis shows number of IPO and technological acquisitions.

The dark line represents the monthly volume of IPOs, while the shaded area below represents the volume of technological acquisitions completed by public firms under 5 years old. As more fully described in the *Data* section, technological acquisitions must involve targets that hold at least one self-generated patent, and which are no more than 50% as large as the acquirer in terms of assets and patents held. All waves in the period of study follow the same pattern, consistent with the findings of a robust empirical literature showing that IPO and M&A waves are highly correlated with each other and to broader economic trends. For example, Lowry et al. (2010) focuses on IPOs, while (Rhodes-Kropf et al., 2005) analyze merger waves and their correlation to broader macroeconomic patterns such as corporate valuations and GDP.

A reliable finding in this literature is that waves end unexpectedly. Brealey and Myers (2003), for example, call the existence of these "financial fashions" an important unsolved puzzle for corporate finance.

There are seven such waves between 1975 and 2009, which technically means there are seven treatment and control cohorts. I assign firms to treatment groups if their IPO was after the midpoint in their respective IPO wave. Conversely, firms that went public before the midpoint are coded as control. For ease of exposition, I refer to treated firms as LATE firms for the remainder of the paper. I refer to control firms as EARLY. Since wave length varies, firms cannot know *ex ante* if they are going public early or late within a wave.

The identification approach is important because, while my baseline argument is straightforward, its empirical study faces a serious endogeneity problem. After all, firms pick the exact date of their IPO, so they probably chose very carefully the type of economic environment in which they go public (Ritter and Welch, 2002). This self-selection makes it difficult to untangle the role played by the environment (versus unobserved heterogeneity) on future characteristics.

An ideal experiment to test the impact of the environment on future innovation strategy would randomize some firms into going public during a time of depressed technological acquisitions and others during active markets.

My quasi-experimental design approaches the randomization goal. All firms in the study go public during an active period, so I do not compare wave to non-wave. However, the firms do not know if they will enjoy a long or short wave, since wave length is unpredictable (Harford, 2005). Consequently, at the moment of IPO, they do not know how close they are to the shock that brings about a dampened acquisitions market. I use timing within early/late IPO wave to sort firms into treatment and control groups and observe their behavior over moving 5-year windows.

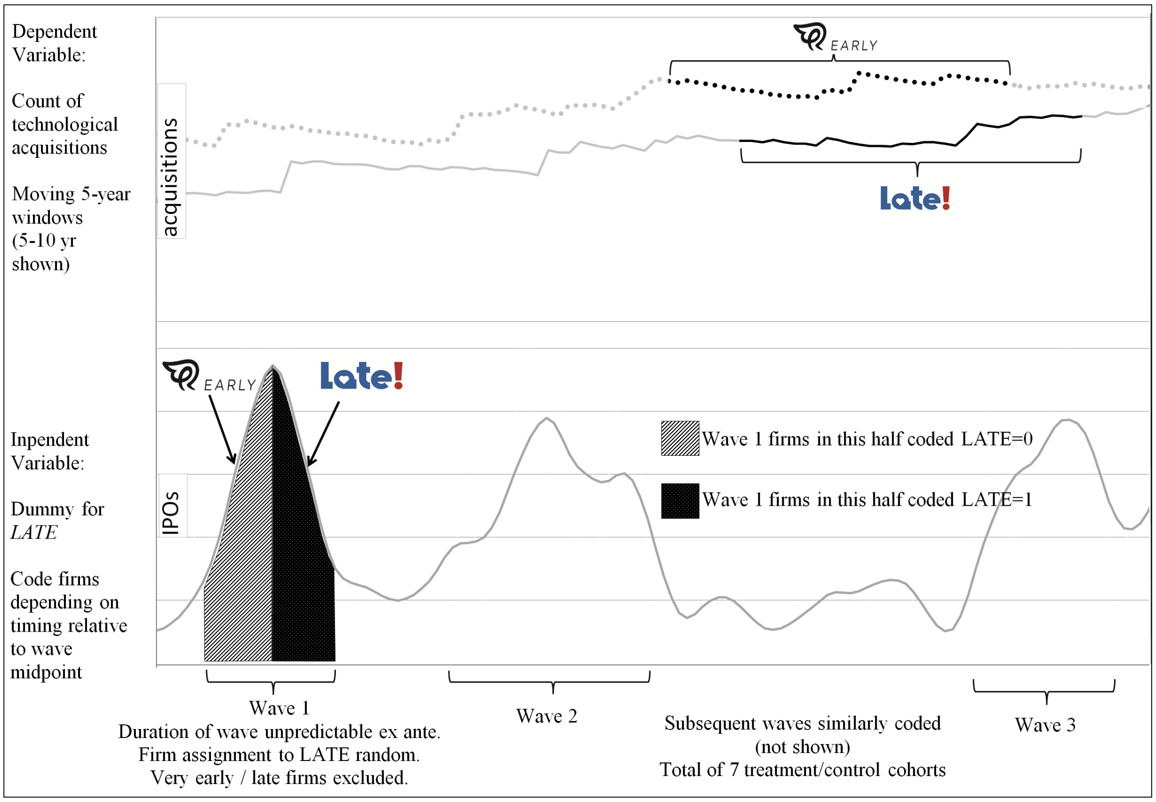

Figure 4: Hypothetical firms "Early" and "Late!" are coded LATE=0 (control) and LATE=1 (treatment) respectively, based on the timing of their IPO relative to midpoint wave. DV compares the count of technological acquisitions between treatment and control groups. The regressions look at moving 5-year windows at 0, 5, 10, 15, and 20 years post-IPO (shown here are the two different measurement windows for each firm in their years 5-10). We expect treated (LATE) firms to engage in fewer acquisitions in the long-run.

I measure within-wave variation only by including controls for each wave.[6] *Figure 2* shows the relationship between the two relevant trends: IPO volume and number of technological acquisitions. It is important to note that the trends shown are smoothed for clarity using a lowess smoother with a bandwidth of 0.4. For reference, *Figure 1*

[6]In robustness tests I also systematically exclude individual waves, and use different definitions of wave, by truncating very early and very late firms within each wave.

shows actual unsmoothed trends, which have much sharper endpoints.

IPOs and plasticity

The period just after an IPO is an ideal scenario to study the intersection between inertia and adaptation because it: a) gives firms increased ability to acquire, which might change firm boundaries; b) disrupts core features of the firm, which might change internal firm structure; c) IPO increases the external scrutiny and pressure to grow, which creates pressures to change.

An IPO removes liquidity constraints, increases legitimacy, and rewards growth. Consistent with this, a growing body of work within the finance literature has documented that firms become heavy acquirers just after going public.[7] For example, Celikyurt and Sevilir (2010) found that pior to IPO, only 19% of firms had made any acquisitions, but that this figure jumped to 74% within 5 years of IPO. But I argue that not all firms respond to IPO in the same way, and that the environment may drive some of this divergence. The main econometric tests of this paper will look at the number of technological acquisitions as a dependent variable.

IPOs change core features of the organization, processes, and structures at many levels, rendering the firm more *plastic* (Gavetti and Rivkin, 2007). At one level, the ownership of the firm changes from concentrated to diluted, potentially disrupting prior relational contracts, internal political structures, and incentive systems. More directly, going public often results in changes in management, as founder-CEO's give up some control, external professional managers come in, and early participants cash out (Stuart and Sorenson, 2003). As I describe in the next section, one possible observable of such changes would be the educational background of top managers. Specifically, I look at the number of MBAs and PhDs in positions of leadership. I argue the MBA managers

[7] See Hovakimian and Hutton (2010) for a review of this literature.

would be more useful to an acquisitive firm, whereas PhDs would be more useful to a more research-oriented firm.

Finally, novel reporting and regulation requirements, in addition to pressure from Wall Street analysts to grow, should change the goals of the firm. For innovative firms, this might reduce the incentives to pursue more uncertain or longer-term projects. This is particularly relevant to my paper, because this pressure against internal development might have countervailing positive effect on the firm's search for external technologies. Consistent with this view, Bernstein (2014) not only found that IPOs increased M&A activity by 300% among patenting firms, but also that going public led to less basic research. His paper is closely related to my study, since we both look at how IPO increases acquisitions and decreases research. However, while Bernstein (2014) looks at the mean effect for all firms that go public (comparing public to non-public) I go on to show that the effects of IPO are not uniform for all firms. As I discuss in the next section, depending on a firm's position in the wave, these changes can move in opposite directions, and seem to be driven by the environmental conditions facing the firm after IPO.

Why the post-IPO environment should have a lasting influence

There is also much theory and evidence within strategy to support the view that inertial pressures can perpetuate patterns that develop during critical periods of a firm's history. As firms become enmeshed in the complex interdependencies of both internal and external activities (Boeker, 1989; Kimberly, 1975), the idiosyncratic webs of specific investments *themselves* become both the firm's critical resources (Zingales, 2000) ,and the organizational "genes" that persist even as the organization grows and changes (Nelson and Winter, 1982). Interdependencies of this sort have been conceptualized under various monikers, such as interactions (Siggelkow and Rivkin, 2006) or "organizational activity patterns" (Romanelli and Tushman, 1986). In general, theoretical perspectives agree that the relationships among multiple dimensions of organizational activity: e.g., strategy, structure, political processes, norms, should be inertial by virtue of their intrinsic organization, above and beyond any deliberate managerial volition.

To summarize the foregoing: *When M&A activity falls shortly after the firm goes public, the firm should respond by pursuing more internal research. It does not invest in its acquisition capabilities as much as it would have, had the M&A cycle continued to boom. Instead, it builds an internal research capability. As a result, temporary responses become more permanent and become part of its core structure going forward.*

3. Data, tests, and results

Data

Information on IPOs comes from Jay Ritter at the University of Florida.[8] I use his data on IPO volume per month to demarcate the beginning and end of the IPO waves. I supplement his data on dates of incorporation for the firms with COMPUSTAT and BvD data (the corrections are minor). I also use his data on first day returns (underpricing) as controls in my regressions.

I construct an inventory of patents, inventors, firm structure, and M&A activity for almost all firms traded in major global stock exchanges. My paper combines data from several sources: (i) patent-level information from the EPOs PATSTAT database; (ii) ownership structure data from ORBIS by Bureau van Djik (BvD); (iii) merger and acquisition data from Thomson Reuters SDC Platinum and Zephyr by BvD; (iv) scientific publications data from Thomson's ISI Web of Knowledge; and (v) accounting information from COMPUSTAT. My dataset leverages the massive efforts of the Eu-

[8] http://bear.warrington.ufl.edu/ritter/ipodata.htm

ropean Patent Office (EPO), which has over several years developed a comprehensive patent database called PATSTAT. This relational database is a snapshot of the EPO master documentation database (DOCDB) with worldwide coverage, containing 20 tables including bibliographic data, citations and family links. Reassignment data is also used to trace the complete history of every patent and ascertain whether it was kept by the original inventing firm or transferred. Thus, I am able to exploit, for the first time, the complete portfolio of patents held by firms.

A major advantage of using PATSTAT over popular resources like the NBER or HBS patent databases (Hall and Jaffe, 2001; Li et al., 2014) lies in the fact that PATSTAT is global and includes applications and priority family relationships. My study looks at the acquisition of technology which is held by small private firms, and these entities are virtually non-existent in the NBER and HBS databases. Small private firms often change names, and their pending applications can be granted to the acquiring firm, which destroys the evidence of who the original applicant was. This severely hampers efforts to trace the sources of external technology. For example, the patents behind Google's Picasa technology all would seem to have been generated by Google, according to traditional databases. But this is because, in the absence of priority family data, we might not know that the original applications were made by Michael Herf, the entrepreneur and founder of Picasa, Inc., (the company) which Google bought and absorbed in 2006. In constructing my dataset, I paid particular attention to linking patent priority families, rather than treating patents in isolation, to find these hidden transfers.

Another important advantage of my data comes from using the Bureau vanDjik (BvD) database to map firm structure for the sample firms. Many firms have complex corporate structures which makes it difficult to draw the boundaries of the firm. For example, within the same firm, some patents may be assigned to headquarters or to wholly-owned subsidiaries. That means that even with perfect matching of assignee to corporate entity, we may still miss the "real" owner of a patent. Johnson & Johnson, Inc., for example, is notorious for having a very decentralized structure where subsidiaries retain title to patents. This undercounts the patent portfolios for many firms. Most importantly, this is not classic measurement error, since it has been shown that the decision to centralize or decentralize patent assignment is strongly correlated with firm structure and innovation strategy (Arora et al., 2014)

The final set matches all patents, applications, and reassignments between 1950 and 2014 and assigned to publicly traded US firms or their wholly owned subsidiaries. This allows me to capture all pre-IPO patenting activity performed by firms, up to 25 years prior to the first IPO in the sample (1975). I match firms to patents by starting with the raw match provided by BVD, and refining the data using a number of original routines. BvD has been working with the EPO since 2010 to match assignee information to their global database on corporate ownership and structure. However, it is important to note that the raw data from BvD is still in the beta trial stage, and required considerable adjustment.

In order to clarify ownership, I used the USPTO reassignment database to verify ownership of each patent. I found that BvD 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.

Corporate ownership structure and transaction data consists of three parts: cross-sectional ownership information from BvD for 2013; M&A data from SDC Platinum and BvD's Zephyr product; and reassignment data from USPTO and PATSTAT.

INSERT TABLES 1 and 2 HERE

Ultimately, the extensive matching of patents to firms is necessary to identify proper technological acquisitions. The importance of a detailed inventory of patents for both acquirers and targets has been emphasized by prior studies (Ahuja and Katila, 2001; Higgins and Rodriguez, 2006), and to date most studies looking strictly at technological acquisitions have exploited small (n¡100) samples. Whereas firms might buy targets for a variety of reasons (e.g., market share, vertical integration, talent) my arguments about the balance between internal and external technology requires that we look only at acquisitions which can substitute for internal research. For similar reasons, I only look at targets which can be thought of as inputs. Clearly, a lateral merger among equals would be beyond of the scope of our discussion, and may change the firm in a number of ways not contemplated here. Thus, I limit targets to firms that are no larger than 50% the size of the acquirer, both in terms of patents and assets held. In all, my sample includes 5,835 acquisitions over the period 1985-2013.

Evidence of persistent difference in acquisitions

Before presenting parametric tests, it is useful to look at the raw data. *Figure 3* shows the stark difference in average external orientation between early and late firms. The graph shows a plot of the average share of external patents (that is, what portion of a firm's monthly flow of patents were sourced via a technological acquisition). On the vertical axis, we have the percentage share average for early and late firms. I equalize time periods so that we can look at all firms in relation to their IPO date, which takes a value of 0 on the horizontal axis.

This allows us to see how the average external share of patents for early and late firms compare before and after going public. We can see that before IPO (value 0 on horizontal), both early and late have very similar shares, about 10%. However, the dashed line shows that going public creates a sharp jump in this ratio for early firms. while the solid line shows that for late firms, the IPO, on average, has a negligible effect on the firms' share of externally acquired patents.

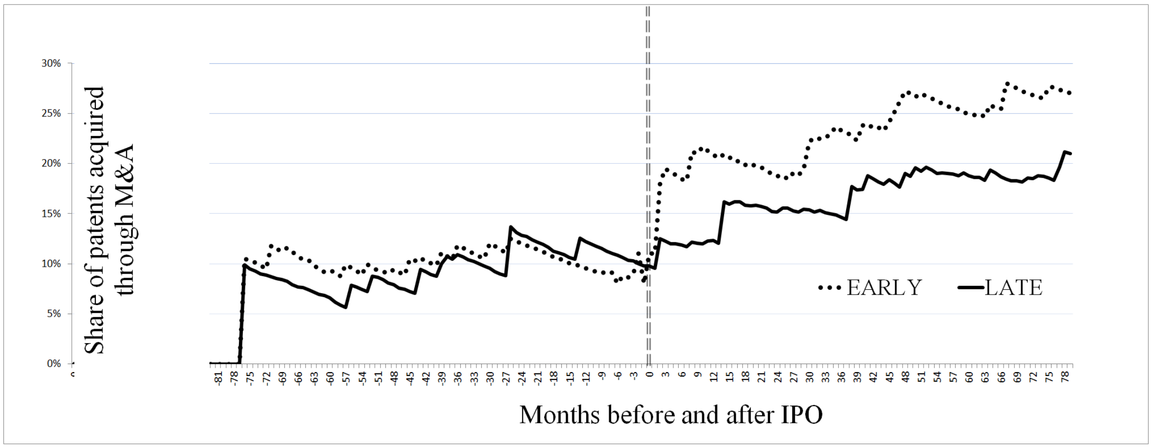

Figure 5: This chart shows the change in share of external patents held by all firms in the sample. The vertical axis shows percentage of patents that came to the firm via an acquisition. On the horizontal axis we see months before and after IPO. Dashed double line denotes the month of IPO. LATE firms in solid plot line. EARLY firms dotted plot line. We can see that on average, early firms increased their technological acquisitions sharply after IPO, whereas LATE firms did not. Horizontal axis spans from 75 months prior to IPO to 77 months after IPO.

Parametric evidence. I am interested in measuring the differences between treated firms, for whom the main explanatory binary variable LATE takes the value of 1, and the control group, for whom LATE takes a value of 0. The main prediction of this study is that we should expect to see late firms engage in fewer technological acquisitions in the long-run, and that these differences will be exclusively due to the timing of their IPO. *Table 3* begins to explores the relationship between LATE and the number of small technological acquisitions that each firm made by looking at the period between years 5 and 10 after IPO. In later tests I will explore for persistence, however here I concentrate on seeing how the relationships between LATE and acquisitions respond to different controls.

On *Column 1* we see that firms on average make just over four such acquisitions.[9] Given that the dependent variable is a count of completed acquisitions, which likely

[9]This is consistent with Celikyurt and Sevilir (2010), who report the number to be 4.3 acquisitions in the first 5 years post IPO.

exhibits overdispersion, I explore the treatment effect of going public closer to the end of a wave using variations of a negative binomial specification (Cameron and Trivedi, 2009).

Incidence ratios show that LATE firms acquire between 39% and 29% fewer technological targets. Incidence ratios on *Column 1* show that LATE firms acquire only 67.24% as many technological targets, relative to early firms. *Column 2* includes controls for pre-IPO patenting characteristics. I include measures for the average originality, generality, and non-patent references of the stock of patents held prior to IPO. These are measures that capture the quality of a firm's research. Including these controls further reduces the ratio of LATE/early to 60.79%, which goes against the possibility that the differences between early and LATE are driven by differences in pre-IPO technological capabilities. *Column 3* shows a slight attenuation once we include firm-level characteristics such as assets, employees, and sales measured at maturity. This makes sense, as firms likely diverge in business and strategic orientations in addition to related to their acquisition activity

INSERT TABLE 3 HERE

I also look at whether the LATE dummy predicts a firm's acquisition rate in the long run. Because firms generally become larger and more acquisitive with age, counts may be harder to interpret. Instead, I compare the ratio of LATE firms to early firms that are in the top quartile of M&A volume for each wave, and within a 5-year moving window that begins on the year of IPO. Looking at quartiles thus helps us see the impact of IPO timing in terms of how likely a firm is to be among the top acquirers for a cohort. In Table 4, *Column 1* shows the effect for firms up to five years post-IPO. Using a moving 5-year window, the magnitude of the negative coefficient on LATE decreases slightly as we move across *Columns 2-5.* Incidence ratios (IRR) are reported and range from 66.92% in years 1-5 to 74.44% in years 15-20. This shows that the differences between early and LATE firms remains quite steady over time, albeit with a slight trend toward convergence. In other words, LATE firms engage in about a third to a quarter fewer technological acquisitions over their life. Not surprisingly, the statistical significance begins to drop as the sample becomes smaller, thus, by *Column 5* we only have 171 firms and significance at the 5% level. These results provide strong evidence of long-run persistence for the impact of LATE on future technological acquisitions. However, the slight attenuating of the impact does not support the view that differences amplify over time.

INSERT TABLE 4 HERE

Evidence of adaptation or selection

The foregoing results have shown that firms exposed to environments unfavorable for acquisitions just after their IPO are roughly 30% less likely to engage in this kind of deal even after they mature. However, this findings could mean different things. Since technological acquisitions are important for firms to access resources, it could mean that LATE firms are simply unlucky, at a disadvantage in terms of acquiring technology, and would exhibit lower performance and survival. This would be consistent with a population ecology view. Alternatively, and according to the arguments presented here, it could be that firms facing times of slim acquisition opportunities might compensate by developing better internal research capabilities. In the next three tables, I explore these two scenarios.

Differences in performance and survival. What is the impact of LATE on survival and performance? Interestingly, I find that there is no impact *per se* of the LATE dummy. In unreported results, a series of tests (using OLS, Negative binomial, and Probit) failed to find significant correlations between LATE and measures for sales, sales growth, or return on assets at maturity. These findings do not support the view that "unlucky" firms were more likely to be selected out. Firms that go late might look and act very differently in terms of their patenting and acquisitions (as shown in the prior results), but this seems an adaptive response, since these differences do not impact their outcomes.

Differences in proxies for internal research. I explore the impact of LATE on patent-level proxies for more basic research. Originality, generality, and references to non-scientific literature (NPL) are widely accepted measures that reflect the degree to which a firm engages in more fundamental versus incremental research (Hall et al., 2005). Table 5 shows that LATE is associated with a significant increase in non-patent references (*NPL*). We see similar results for *generality* and *originality.* These regressions are OLS with a full gamut of controls for pre and post IPO characteristics. Note that whereas the association between acquisitions just after IPO and acquisitions later in life is relatively intuitive, and consistent with learning and resource accumulation theories, for us to find divergence in terms of type of research performed is strongly supportive of a more complicated adaptive view.

Put simply, it seems that firms which might appear "unlucky" at first (having gone public close to an economic slowdown), actually manage to compensate by developing better internal research capabilities. It is important to note that I do not measure capabilities, but rather measure proxies for research effort. However, to putting these findings on research effort together with the findings on performance suggests that the LATE firms have developed better research capabilities. Otherwise, it would be hard to explain their ability to be economically on par with early firms, while doing fewer technological acquisitions and spending more effort on research.

INSERT TABLE 5 HERE

While the main tests in the paper split firms into early and late based on their position within a wave, the core argument is that the shock comes at the end of the wave. If this is the case, we should expect that the temporal "distance" from the end of each wave should be correlated with our variables of interest. To check this, I run the exact same regressions as in *Table 5*, while replacing the LATE dummy with a count measure of how many months between a firm's IPO and the end of its wave. As *Table 6* shows, the results are very similar.

INSERT TABLE 6 HERE

Differences in top management. Managers can be one locus of persistence in organizations. For example, seminal work in imprinting has shown founders bring organizational "blueprints" become part of the firm's core structure (Hannan et al., 1996), but that these effects may attenuate over time. However there is not much known about how the environment shapes the firm's management post-founding, as the founder's influence fades. Thus, I explore whether IPO timing is also related to the composition of top management. The logic is that a firm should have consistent supporting structures for its sets of activities (Drazin and de Ven, 1985; Siggelkow, 2011), and that management is part of this structure. If firms develop external(internal) capabilities, then we should expect their management to reflect the firm's orientation. I explore the impact of LATE on the composition of top management at maturity. I measure top management for firms between 5 and 10 years of age as of 2013, and include the educational background of its managers as observed 2013. Data limitations prevent me from observing educational background across moving windows, as in the acquisition analysis.

I perform negative binomial regressions to look for differences in education of top management. *Table 7* shows the impact of the LATE dummy on the characteristics of top management as of 2013. The dependent variable is a count of how many top managers had either an MBA (Column 1) or a PhD in a scientific field (Column 2).

I measure top management for each firm during the window between 5 and 10 years post IPO. Coefficient estimates for negative binomial regressions are exponentiated and reported here as incidence ratios. For managers of a given type (MBA or PhD), incidence ratios reported can be interpreted as the ratio of (count of managers for early firms)/(count of managers for late firms). *Column 1* shows that LATE firms have only 33.4% as many MBA managers relative to early firms. On the other hand, *Column 2* shows that LATE firms have a 34.7% more managers with a science or engineering PhD relative to early firms.

INSERT TABLE 7 HERE

Other tests

Variation within *early* and *late*. Although I find no significant difference in performance or survival between early and LATE firms, I am interested in whether there is variation within each half of the wave. Specifically, not all early firms are heavy acquirers, and conversely, not all LATE firms are strong researchers. This, I create a dummy called CONFORM which takes the value of one for firms that pursue the dominant strategy, conditional on being early or late. In other words, I explore what happens to firms that do not get exhibit the same patterns as the with the rest of their early/LATE cohort. Firms conform if they are both LATE=1 and in the bottom quartile of acquisitions. Conversely, firms conform if they are both LATE=0 and in the top quartile of acquisitions. Interestingly, I find a strong and significant positive relationship between CONFORM and both survival and performance. As Table 8 shows, I find that conforming firms have an increased chance of survival of about 25% when measured at the mean. These results are not sensitive to the firm's initial R&D investment (lxrd1), or age (lage). It might be that firms pay a price for trying to overcome inertia, if for example they begin down one path just after IPO, but then change and the reorganization fails. Alternatively, firms my only undertake significant change when faced with poor performance (Romanelli and Tushman, 1986). Establishing the direction of causation is important, but beyond the scope of this paper. Current ongoing work will continue to explore these findings.

INSERT TABLE 8 HERE

Robustness tests. Despite the argument that firms cannot know their place within a wave *ex ante*, it is still possible that some omitted variable drives some firms to be quicker to go public within a wave, and that this is also correlated with future orientation. To mitigate this concern, I run Probit tests for selection on several observed characteristics of both the firms themselves (pre-IPO) and their patents (pre-IPO). As shown in Table 9, I find no difference in terms of non-patent citations (a standard measure of scientific orientation and basicness), originality, or generality. This suggests that firms in the sample were not systematically different between treatment and control groups.

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 2 months of a Wave, in order to mitigate concerns that firms have private information that allow them to predict the beginning or end of waves. Results are no different for these specifications, however the significance is reduced in some coefficients due to smaller sample sizes. I also systematically exclude individual waves from the analysis in all main specifications to ensure that no single wave is driving the results. This is largely a redundant test, since the specifications already capture within-wave variation through wave dummies. Not surprisingly, removing individual waves has no effect on the results.

INSERT TABLE 9 HERE

5. Discussion

Innovation has been an important setting for thinking about organizational evolution and capabilities for a number of reasons: innovation is important (Schumpeter, 1944), takes time to master (Arrow, 1962b), and exhibits strong path-dependency (Cohen and Levinthal, 1989). Within strategy, a core tension in innovation is the extent to which current capabilities allow a firm to compete, but may also hinder the exploration of future technological solutions (Christensen, 2013; Katila, 2002; Levitt and March, 1988). Firms buy external knowledge to complement their internal efforts while selling or licensing technology that cannot be optimally exploited internally (Arora and Gambardella, 1994; Granstrand and Sjölander, 1990). Much work in the innovation literature exploring these dynamics has focused on how attributes of the technology (e.g., appropriability and patentability), as well as institutional and market conditions, influence entrants' and incumbents' decision to compete through internal development or cooperate via acquisition (Arora et al., 2001; Cohen et al., 2000; Gans and Stern, 2003; Pisano, 1990).

However, this transaction-oriented branch of the innovation literature has largely side-stepped issues of persistent firm differences. While firm differences are sometimes discussed in this literature, they are generally treated as orthogonal to the core arguments. For example some explicitly assume "memoryless" R&D investments and firms that can equally increase or decrease their R&D bargaining power Gans and Stern (2000) . Similarly, Arora et al. (2001) acknowledges that *absorptive capacity*, *not invented here*, and similar firm-specific constructs should interact with markets for technology, though these are never included in their formal models. In other words, it is assumed that all firms come to the same decision (e.g., make or buy) given the same set of technological and market circumstances, and that having made a decision, firms do not face significant barriers to implementation.

In contrast to the transaction-oriented view (*buy*), the resource-based view on innovation (*make*) focuses on the accumulation of firm-specific idiosyncratic experiences and capabilities over time (Penrose, 1959). For example, regular investments in R&D have been shown to increase firms' ability to access and integrate external knowledge (Cohen and Levinthal, 1990), and there is evidence that competencies arise through experience and reside in the hard-to-change organizational structure of the firm (Henderson and Cockburn, 1994). This is a type of "memory" effect, and we should expect that more mature firms would be less responsive to exogenous factors (e.g., nature of technology and institutional environment) in their make/buy calculus. In other words, these firms are subject to inertial pressures that limit their ability to adapt to the environment.

In this paper I have argued that innovative firms develop their technological orientation through a sequential process of transaction mechanisms and resource accumulation mechanisms, and that the importance of these varies depending on the life stage of the firm. During times of change, such as IPO, transaction mechanisms orient the firm to the environment. After that, resource accumulation mechanisms maintain a degree of inertia. While recent theoretical arguments have identified the need for such cross-framework integration (Argyres, 2011), to my knowledge this is the first large-scale empirical study to undertake such an endeavor.

Looking at the population of firms in the economy, we see stark heterogeneity consistent with this view (Arora et al., 2014). If firms were primarily adaptive, then we would expect that within an industry they would tend towards convergence. On the other hand, if they were primarily inertial, we would expect that those that do not fit with the environment would be selected out, once again leading towards homogeneity. The findings I have reported in this paper are consistent with the diversity of firms that we see in the world.

Beyond the field of innovation, the interdisciplinary implications of this paper are also significant. There are divergent views on what *founding* and *imprinting* literatures are, and this paper does not claim to map perfectly with any of them. Nonetheless, my results should contribute to many of these streams, by showing large-scale evidence consistent with the imprinting hypothesis, but occurring in a non-founding setting. Furthermore, within the context of imprinting and founding conditions, the inertial view has been brought to bear (even by Stinchcombe himself) to argue that a one-shot luck of the draw at founding determines survival and failure. However, expanding concepts like imprinting to include subsequent periods of alternating plasticity and ossification allows for a more nuanced view, where adaptation and inertia can take turns charting a firm's path. Such reconciliation can help us bridge some potentially false dichotomies across disciplines. After all, even Hannan and Freeman's population ecology manifesto (1977), often seen as the antithesis to strategic management's faith in volition, admits that: "a complete theory of organization and environment would have to consider both adaptation and selection, recognizing that they are complementary processes."

My findings are also informative to managers, who must constantly "discriminate between what is and is not controllable" (Gavetti and Levinthal, 2004; Winter, 1987). In this regard, the present study is helpful in guiding organizational self-awareness. For example, firms that ramp up in times of depressed acquisition markets may have internal obstacles to overcome along the way of implementing an acquisition strategy, such as entrenched roles and compensation structures that reward internal development. These may not be responsive to a top-down decree to change strategy. 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 waves, my findings could be useful for firms considering an IPO during a non-wave period. If a firm has particularly strong internal research opportunities, then an off-wave IPO may be desirable. 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.

This paper has provided strong evidence of how quickly firms might cement their technological orientation This brief but important sensitive period calls for future work into the conditions under which inertia and adaptation interact. Theoretically, this study draws on economics, finance, RBV and evolutionary theory, and thus highlights the value of drawing on literatures that do not often speak to each other. From an innovation perspective, this paper paper builds on recent work that has shown persistence heterogeneity in organization of R&D, and suggests a potential mechanism behind the empirical findings.

There is much that we do not know about how the timing of events moderates their impact on a firm‘s evolution. There are likely likely many other punctuated windows that we should be looking at. Mergers and acquisitions in particular, can be transformative events, and future work should look at similar windows, for example succession after founder exit or bankruptcy.

6. Conclusion

This study has shown that the timing of IPO mattered for the population of firms that went public between 1975 and 2008. Firms that went late during waves in this period engaged in fewer technological acquisitions in the long run, and engaged in more internal research. The econometric tests sought to mitigate concerns about selection, and it is argued that the observed differences among late firms was due to their exposure to less opportunities to grow via technological acquisitions in the period after going public.

While it may be uncontroversial to suggest that past events would affect future performance and organization characteristics, there has been surprisingly little empirical evidence to document how and when this actually occurs. Thus, this paper makes two novel contributions. First, by focusing on a window of time during which firms are still evolving, but which is removed from their actual founding, it isolates the role of the environment from potential confounds, such as founder effects. Second, it shows that the window after IPO is a very sensitive period during which firms adapt to the environment, and that once this short window closes, very strong inertia takes over. This is empirically shown by the stark difference among firms which experienced differences in exposure that amounted to, on average, about 18 months. This is a novel finding that should stimulate future work on the origins of firm heterogeneity.

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Appendix A: Tables

Table 1: Descriptive statistics

	mean	sd	min	max
technological acquisitions	.950	1.140	0	30
private technological acquisitions	.935	.656	0	25
R&D expenditures ($mill)	.589	.988	0	7.83
wave number	3.995	1.470	1	7
age postIPO	13.023	5.838	6	34
age at IPO	5.811	4.065	1	15
assets	2,555	17477	0	691,063
sales	1,463	7866	0	352,369
LATE	.512	.499	0	1
Observations	14,498			

Note: Unit of observation is firm-year

Table 2: Correlation matrix

	tech acq	private tech acq	R&D	patents	wave number	age postIPO	age at IPO	assets	sales	LATE
tech acq	1.00									
private tech acq	0.66***	1.00								
	(0.00)									
R&D	0.10***	0.03**	1.00							
	(0.00)	(0.00)								
patents	0.37***	0.20***	0.29***	1.00						
	(0.00)	(0.00)	(0.00)							
wave number	-0.01	-0.04***	0.28***	-0.06***	1.00					
	(0.19)	(0.00)	(0.00)	(0.00)						
age postIPO	0.06***	0.01	-0.10***	0.06***	-0.45***	1.00				
	(0.00)	(0.28)	(0.00)	(0.00)	(0.00)					
age at IPO	0.03**	0.01	-0.01	0.02**	-0.05***	0.02**	1.00			
	(0.00)	(0.21)	(0.12)	(0.01)	(0.00)	(0.00)				
assets	0.11***	0.03***	0.15***	0.16***	0.00	0.06***	0.00	1.00		
	(0.00)	(0.00)	(0.00)	(0.00)	(0.66)	(0.00)	(0.82)			
sales	0.16***	0.06***	0.24***	0.23***	-0.03**	0.12***	-0.04***	0.63***	1.00	
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		
LATE	-0.06***	-0.09***	-0.02**	0.01***	-0.20***	0.05***	-0.02*	0.05***	0.04***	1.00
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	
Observations	14568									

Note: P-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: Impact of late-wave dummy on number of small tech acquisitions completed between years 5 and 10 post IPO. Incidence ratios on *Column 1* show that LATE firms acquire only 67.24% as many technological targets, relative to early firms. *Column 2* includes the following controls for firm-level pre-IPO patenting characteristics: average originality, generality, and non-patent references (for the stock of patents held prior to IPO. These are measures that capture the quality of a firm's research. Including these controls further reduces the ratio of LATE/early to 60.79%, which goes against the possibility that the differences between early and LATE are driven by differences in pre-IPO technological capabilities. *Column 3* shows a slight attenuation once we include firm-level characteristics such as assets, employees, and sales measured at maturity. This makes sense, as firms likely diverge in business and strategic orientations in addition to related to their acquisition activity

	small deals	*small deals*	*small deals*
dummy for late in wave	-0.396***	-0.498***	-0.347***
	(0.114)	(0.137)	(0.118)
mean value for DV	4.183	4.963	4.456
incidence ratio	0.672***	0.608***	0.707***
	(0.076)	(0.084)	(0.087)
control pre-IPO NPL references	No	Yes	Yes
control pre-IPO originality	No	Yes	Yes
control pre-IPO generality	No	Yes	Yes
control pre-IPO firm characteristics	Yes	Yes	Yes
control post-IPO firm characteristics	No	No	Yes
NAICS Codes	Yes	Yes	Yes
individual wave dummies	Yes	Yes	Yes
Observations	907	633	633

Unit of observation is the firm.
Standard errors in parentheses are robust to arbitrary heteroskedasticity.
Results are virtually unchanged using classical standard errors
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: This table explores how differences in technological acquisitions between early and LATE firms persist over time. *Column 1* shows the effect for firms up to five years post-IPO. Using a moving 5-year window, the magnitude of the negative coefficient on LATE remains fairly constant on *Columns 2-5.* Incidence ratios (IRR) are reported and range from 66.92% in years 1-5 to 74.44% in years 15-20. In other words, LATE firms engage in about a third to a quarter fewer technological acquisitions over the study period. These results provide strong evidence of long-run persistence for the impact of LATE on future acquisitions.

	(1) top 4tile yrs 1-5	(2) top 4tile yrs 5-10	(3) top 4tile yrs 10-15	(4) top 4tile yrs 15-20	(5) top 4tile yrs 20+
LATE dummy	-0.402***	-0.385***	-0.335***	-0.295***	-0.326**
	(0.139)	(0.151)	(0.125)	(0.117)	(0.158)
incidence ratios	0.669***	0.680***	0.715***	0.744***	0.722**
	(0.093)	(0.097)	(0.097)	(0.123)	(0.186)
ln(age at IPO)	0.147	0.248	-0.018	-0.626*	-0.526
	(0.189)	(0.233)	(0.341)	(0.350)	(0.424)
ln(age)	-1.538***	-2.561***	-0.619	2.017	2.682
	(0.588)	(0.907)	(1.541)	(1.473)	(1.679)
1st wave	0.000	0.000	0.000	0.000	0.0000
	(.)	(.)	(.)	(.)	(.)
2nd wave	-0.193	-0.180	-0.199	-0.200	-0.1706
	(0.507)	(0.517)	(0.585)	(0.674)	(0.7120
3rd wave	0.536	0.383	0.680	0.950*	1.074*
	(0.362)	(0.398)	(0.448)	(0.570)	(0.563)
4th wave	0.304	-0.146	0.554	1.448**	
	(0.383)	(0.484)	(0.645)	(0.715)	
5th wave	0.024	-0.544	0.535		
	(0.431)	(0.565)	(0.839)	(0.888)	
6th wave	0.109	-0.771	0.518		
	(0.514)	(0.720)	(1.134)		
7th wave	0.217	-0.198			
	(0.679)	(0.862)			
pre IPO firm chars	Yes	Yes	Yes	Yes	Yes
post-IPO firm chars	Yes	Yes	Yes	Yes	Yes
NAICS	Yes	Yes	Yes	Yes	Yes
Observations	1211	806	646	325	171
r2	0.339	0.386	0.476	0.659	0.730

Unit of observation is firm. Standard errors are robust to arbitrary heteroskedasticity
Results are virtually unchanged using classical standard errors
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: This table shows the relationship between LATE and patent generality (gen), originality (orig), and non-patent scientific references (NPL). *Columns 1-3* show a positive impact of LATE on all measures. *Columns 4-6* include additional controls for assets and R&D expenditures at time of IPO, as well as patent stock in 2013 and dummy for whether the firm survived. The additional controls marginally strengthen the coefficients, and increase the significance level from 0.05 to 0.01 percent. This is consistent with the view that results are not driven by pre-IPO characteristics nor by survival or growth.

	(1) gen	(2) orig	(3) NPL	(4) gen	(5) orig	(6) NPL
LATE dummy	0.033**	0.070***	0.049**	0.035***	0.072***	0.060***
	(0.015)	(0.021)	(0.019)	(0.013)	(0.020)	(0.019)
DV mean value	0.427	0.614	0.306	0.427	0.614	0.306
(effect of LATE on DV)	(7.73%)	(11.4%)	(16.0%)	(8.20%)	(11.73%)	(19.61%)
ln(age at IPO)	-0.007	0.015	0.004	-0.002	0.023	0.013
	(0.017)	(0.020)	(0.022)	(0.018)	(0.020)	(0.021)
ln(assets)	-0.005	-0.015	-0.021*	-0.003	-0.014	-0.018
	(0.008)	(0.014)	(0.011)	(0.008)	(0.016)	(0.012)
ln(R&D spend)	0.008	0.024*	0.058***	0.003	0.012	0.030***
	(0.007)	(0.014)	(0.010)	(0.009)	(0.014)	(0.011)
R&D / sales	0.028	0.193**	0.214***	0.026	0.171**	0.156***
	(0.041)	(0.081)	(0.063)	(0.038)	(0.075)	(0.056)
ln(employees)	-0.028**	-0.011	-0.040**	-0.036**	-0.010	-0.034**
	(0.012)	(0.014)	(0.016)	(0.014)	(0.018)	(0.015)
ln(patents)	0.013**	0.010	-0.009	0.030***	0.022	0.000
	(0.006)	(0.008)	(0.008)	(0.010)	(0.017)	(0.013)
ln(sales)	-0.021	-0.057*	-0.189***	-0.011	-0.042	-0.164***
	(0.023)	(0.035)	(0.033)	(0.027)	(0.043)	(0.036)
surviving in 2013				0.001	0.048	0.064**
				(0.021)	(0.031)	(0.028)
ln(age 2013)				0.019*	-0.001	0.022
				(0.011)	(0.016)	(0.018)
ln(assets at IPO)				-0.001	-0.008	-0.014
				(0.007)	(0.011)	(0.009)
ln(R&D spend at IPO)				0.015**	0.021*	0.038***
				(0.007)	(0.011)	(0.008)
ln(patent stock 2013)				-0.026***	-0.021	-0.021
				(0.009)	(0.018)	(0.015)
NAICS	Yes	Yes	Yes	Yes	Yes	Yes
year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	192,648	255,895	255,468	182,446	242,348	241,952
r2	0.111	0.068	0.079	0.119	0.071	0.084

Standard errors in parentheses clustered at firm level. OLS regressions.

For binary dependent variable in models 3 and 6, results are robust to Probit specification.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: This table shows the relationship between time to wave-end and patent generality (gen), originality (orig), and non-patent scientific references (NPL). These are the same specifications as Table 5, replacing the DV with the count of months between IPO and end of wave. All the results are similar to Table 5. However, interpreting the coefficients is less-straightforward. Given that the average wave lasts 18 months, one potential way to conceptualize the impact is to multiply the percentage (monthly effect) coefficients by 18. Importantly, this yields results that are very similar in magnitude as those shown in Table 5.

	(1) gen	(2) orig	(3) NPL	(4) gen	(5) orig	(6) NPL
distance	-0.001*	-0.002**	-0.002*	-0.002***	-0.003***	-0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
DV mean value	0.427	0.614	0.306	0.427	0.614	0.306
(effect/month on DV)	(0.24%)	(0.33%)	(0.65%)	(0.47%)	(0.49%)	(1.0%)
ln(age at IPO)	-0.007	0.009	-0.002	0.002	0.024	0.017
	(0.018)	(0.021)	(0.025)	(0.018)	(0.020)	(0.021)
ln(assets)	-0.005	-0.012	-0.016	-0.004	-0.017	-0.021
	(0.008)	(0.015)	(0.012)	(0.008)	(0.017)	(0.013)
ln(R&D spend)	0.008	0.029*	0.065***	0.003	0.014	0.031***
	(0.007)	(0.018)	(0.012)	(0.009)	(0.015)	(0.012)
R&D / sales	0.038	0.233***	0.258***	0.032	0.185**	0.166***
	(0.042)	(0.082)	(0.069)	(0.039)	(0.076)	(0.058)
ln(employees)	-0.027**	-0.010	-0.041**	-0.036**	-0.009	-0.033**
	(0.013)	(0.016)	(0.018)	(0.014)	(0.019)	(0.015)
ln(patents)	0.011**	-0.002	-0.024**	0.031***	0.023	0.002
	(0.006)	(0.010)	(0.010)	(0.010)	(0.018)	(0.014)
ln(sales)	-0.020	-0.058	-0.192***	-0.011	-0.040	-0.165***
	(0.024)	(0.040)	(0.040)	(0.027)	(0.045)	(0.038)
ln(age)				0.019	-0.003	0.021
				(0.012)	(0.017)	(0.018)
ln(assets at IPO)				-0.001	-0.007	-0.013
				(0.007)	(0.011)	(0.009)
ln(R&D spend at IPO)				0.015**	0.020*	0.038***
				(0.007)	(0.012)	(0.009)
ln(patent stock 2013)				-0.028***	-0.023	-0.023
				(0.009)	(0.019)	(0.016)
surviving in 2013				0.003	0.053	0.069**
				(0.021)	(0.033)	(0.030)
Observations	192646	255889	255462	182445	242343	241947
r2	0.110	0.061	0.074	0.119	0.069	0.084

Standard errors in parentheses clustered at firm level. OLS regressions.

For binary dependent variable in models 3 and 6, results are robust to Probit specification.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: This table shows the impact of the LATE dummy on the characteristics of top management. The dependent variable is a count of how many top managers had either an MBA (Column 1) or a PhD in a scientific field (Column 2), for firms between 5 and 10 years of age as of 2013. Data limitations prevent me from observing educational background across moving windows, as in the acquisition analysis. Coefficient estimates for negative binomial regressions are exponentiated and reported here as incidence ratios. For managers of a given type (MBA or PhD), incidence ratios reported can be interpreted as the ratio of (count of managers for early firms)/(count of managers for late firms). *Column 1* shows that LATE firms have only 33.4% as many MBA managers relative to early firms. On the other hand, *Column 2* shows that LATE firms have a 34.7% more managers with a science or engineering PhD relative to early firms.

	count of MBA mgrs (1)	*count of PhD mgr* . (2)
LATE dummy	0.333***	
	(0.140)	
LATE dummy		1.347**
		(0.192)
control pre/post-IPO firm characteristics	Yes	Yes
IPC Codes	Yes	Yes
NAICS Codes	Yes	Yes
individual wave dummies	Yes	Yes
Observations	274	274

Unit of observation is the firm.
Exponentiated coefficients (incidence rate ratios).
Standard errors are robust to arbitrary heteroskedasticity
Results are virtually unchanged using classical standard errors
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Although I find no significant difference in performance or survival between early and LATE firms, I am interested in whether there is variation within each half of the wave. Specifically, not all early firms are heavy acquirers, and conversely, not all LATE firms are strong researchers. This, I create a dummy called CONFORM which takes the value of one for firms that pursue the dominant strategy, conditional on being early or late. Firms conform if they are both LATE=1 and in the bottom quartile of acquisitions. Conversely, firms conform if they are both LATE=0 and in the top quartile of acquisitions. I find a strong and significant positive relationship between CONFORM and both survival and performance. I find that conforming firms have an increased chance of survival of about 25% when measured at the mean. These results are not sensitive to the firm's R&D investment or age at IPO.

	(1) surv	(2) surv	(3) surv	(4) surv	(5) surv
CONFORM	0.164***	0.182***	0.183***	0.183***	0.180***
	(0.036)	(0.033)	(0.034)	(0.034)	(0.036)
ln(age at IPO)	-0.021		-0.041	-0.041	-0.028
	(0.029)		(0.028	(0.028)	(0.029)
ln(assets at IPO)	0.000			0.000	0.000
	(.)			(.)	(.)
ln(R&D at IPO)	0.089***				0.089***
	(0.011)				(0.011)
wave + firm chars	Yes	Yes	Yes	Yes	Yes
	(.)	(.)	(.)	(.)	(.)
Observations	723	930	880	880	723
r2	0.370	0.306	0.301	0.301	0.358

Unit of observation is the firm.

Standard errors are robust to arbitrary heteroskedasticity

Results are virtually unchanged using classical standard errors

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Probit test for selection into treatment group: Do pre-IPO non-patent references, originality and generality measures predict dummy for late in wave? Despite the quasi-experimental setting, it is possible that some firms self-select to go early or LATE. This might driving the relationship between LATE firms and their differences in patenting and M&A. To mitigate this concern, I run Probit tests to see whether the type of research performed by the firms prior to IPO predicts the sorting into early or LATE. I use average originality, generality and non-patent citations for the stock of patents of firms pre-IPO. These are widely accepted proxies for quality of research, and if firms are less research intensive before IPO, it would make sense that they are more acquisitive and less research intensive after IPO. The table shows that none of the measures of research quality are significantly correlated with the LATE dummy. This suggests that firms' pre-IPO patenting was not systematically different between early and LATE firms.

	.	*Prob(late=1)*	*.*
	(1)	(2)	(3)
NPL share pre-IPO	-0.380		
	(0.582)		
firm-level average originaltiy pre-IPO		0.797	
		(0.551)	
firm-level average generality pre-IPO			0.687
			(0.465)
control pre-IPO firm characteristics	Yes	Yes	Yes
IPC Codes	Yes	Yes	Yes
NAICS Codes	Yes	Yes	Yes
individual wave dummies	Yes	Yes	Yes
Observations	341	292	279

Unit of observation is the firm.

Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix B: Figures

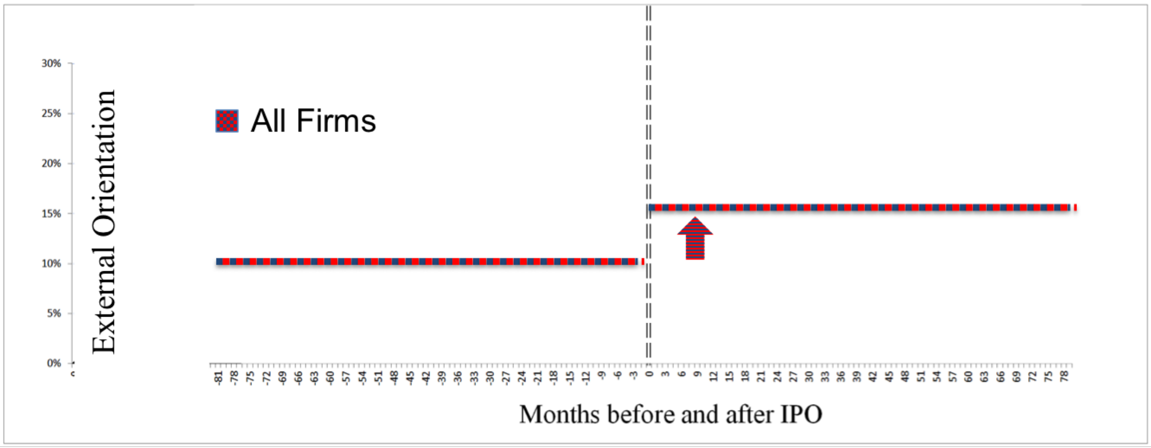

Figure 1: This figure shows a stylized depiction of the shift in technological orientation documented by Bernstein (2014).

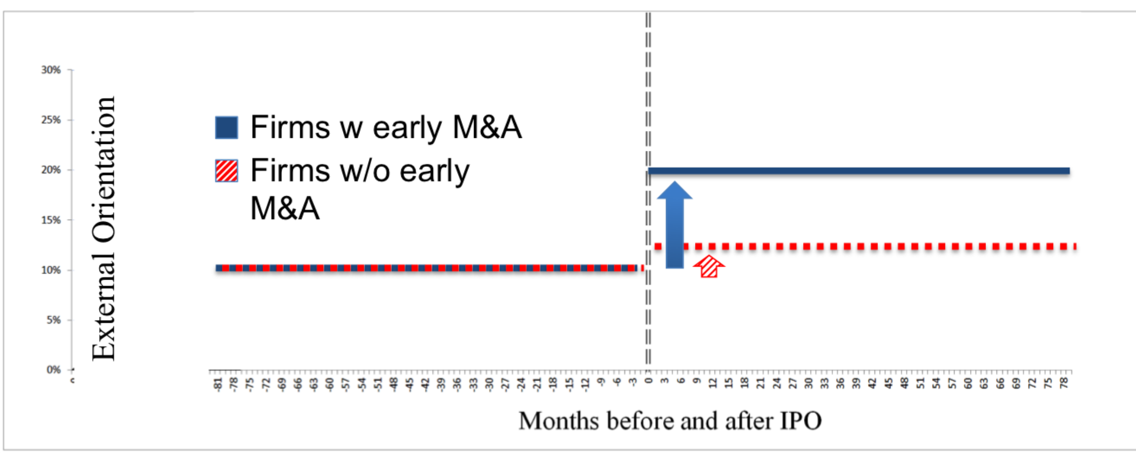

Figure 2: This figure shows a stylized depiction of the predicted differential shift in technological orientation: If firms late to the cycle have fewer options to acquire, they may compensate by investing in internal R%D, leading them down a different trajectory.

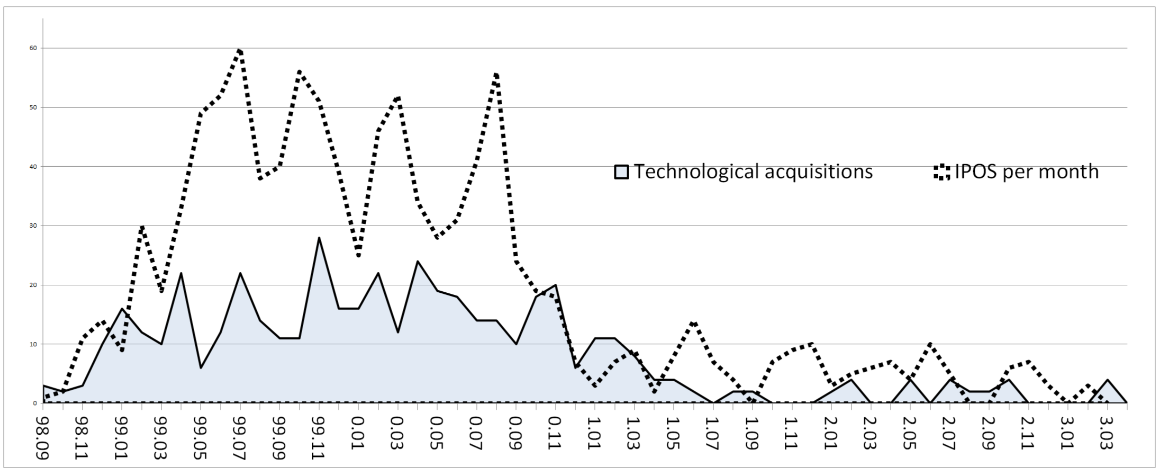

Figure 3: This figure illustrates the high degree of correlation between IPO waves and intensity of technological acquisitions, as observed during the 1999-2000 wave. Importantly, both IPO and acquisitions end sharply and almost at the same time. The horizontal axis shows months, and the vertical axis shows number of IPO and technological acquisitions.

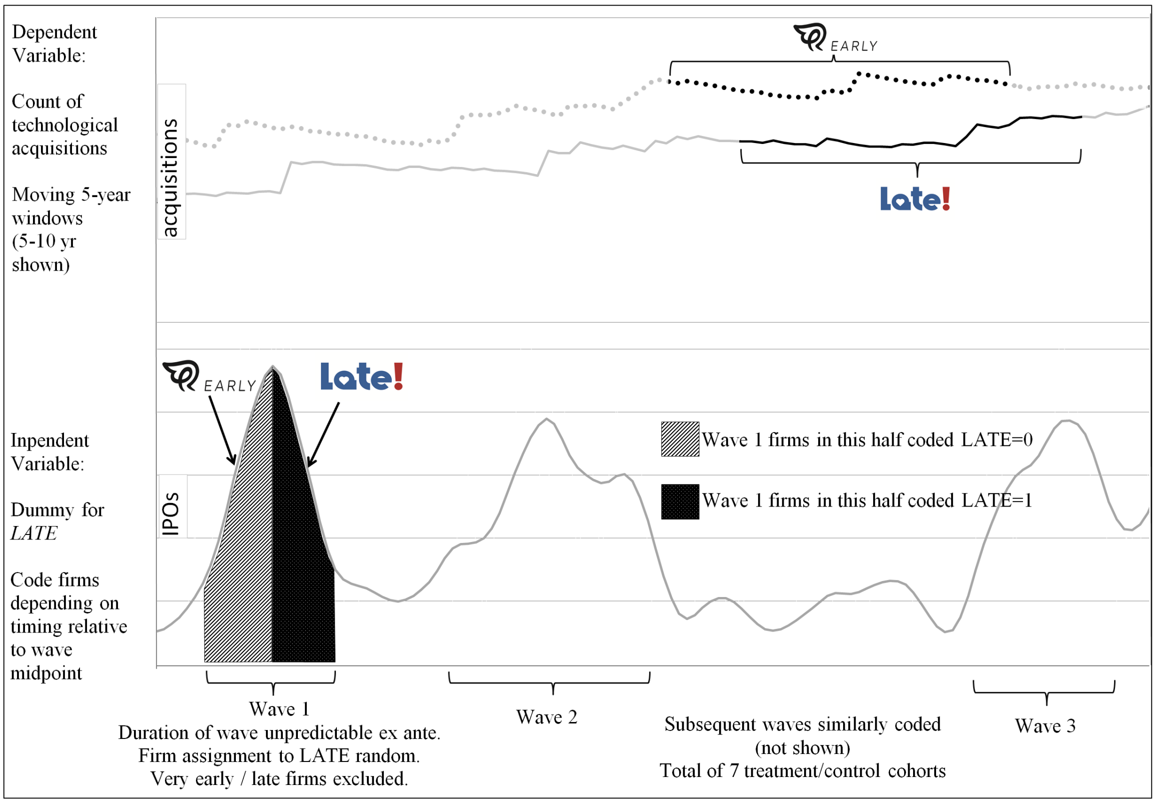

Figure 4: Hypothetical firms "Early" and "Late!" are coded LATE=0 (control) and LATE=1 (treatment) respectively, based on the timing of their IPO relative to midpoint wave. DV compares the count of technological acquisitions between treatment and control groups. The regressions look at moving 5-year windows at 0, 5, 10, 15, and 20 years post-IPO (shown here are the two different measurement windows for each firm in their years 5-10). We expect treated (LATE) firms to engage in fewer acquisitions in the long-run.

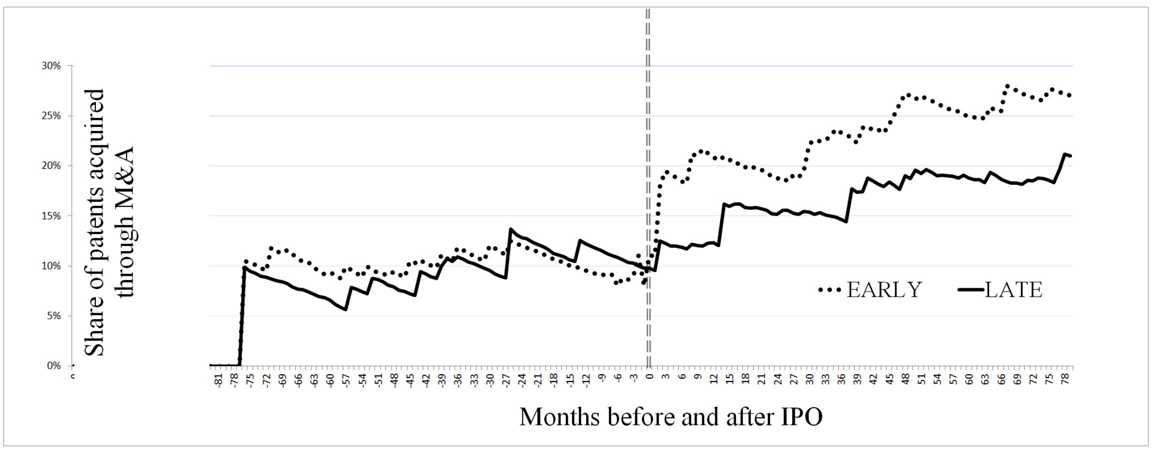

Figure 5: This chart shows the change in share of external patents held by all firms in the sample. The vertical axis shows percentage of patents that came to the firm via an acquisition. On the horizontal axis we see months before and after IPO. Dashed double line denotes the month of IPO. LATE firms in solid plot line. EARLY firms dotted plot line. We can see that on average, early firms increased their technological acquisitions sharply after IPO, whereas LATE firms did not. Horizontal axis spans from 75 months prior to IPO to 77 months after IPO.