Product Life Cycles in Corporate Finance

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ABSTRACT

We build a dynamic text-based model of the product life cycle aggregated to the firm level. Motivated by theory, we model five stages: product innovation, process innovation, maturity, decline, and delisting. We find that firms, on average, follow identifiable transitions through the cycle as they age, however major shocks can disrupt, reverse, or accelerate this progression. A firm's position in the life cycle has material consequences for its investment policies, the sensitivity of its investment to Tobins' Q, its acquisition strategy, and its longer-term outcome. Regarding investment, a conditional investment-Q model vastly outperforms a simple investment-Q model in predicting investment, and moreover the advantage of the conditional model is growing in magnitude during our sample as firms are becoming larger and more complex. Overall our findings document a first-order role played by product life cycles in shaping an array of important corporate finance decisions.

1 Introduction

Understanding how, why, and when firms grow and invest is a seminal research question in corporate finance and economics. Although there are some noteworthy exceptions (Ericson and Whited (2012) and Peters and Taylor (2015) for example), decades of empirical research have had to rely on highly aggregated measures of investment opportunities such as ratios of market to book values. A critical issue is that such ratios are influenced by issues other than investment opportunities: barriers to entry, demand shocks, heterogeneous production technology, and global penetration. Investment options are also heterogeneous. Some entail the development of new products, the development of better production technology, or even the option to acquire existing firms to harvest synergies. Simple market to book ratios offer inadequate flexibility to model the heterogeneous consequences these different types of growth options might have on a firm.

We propose that product life cycle theories have important predictions that can greatly improve our ability to research these issues. Suppose for example, following Abernathy and Utterback (1978), that firms begin life with a focus on product innovation, and they later transition to process innovation, maturity, and ultimately decline. If we knew which state a firm's product portfolio was in, we should be able to characterize the likely composition of its growth opportunities. For example, firms in the product innovation stage have growth options relating to new product development. We would predict higher R&D and higher market values. Firms focusing on process innovation have growth options that are more related to reducing production costs, and their growth options would derive most from cost cutting opportunities and capital expenditures to create less costly production methods.

Firms in later mature stages would be characterized by an absence of both aforementioned internal investment opportunities. Instead such firms might experience increases in their Tobins Q when they have more external growth options through acquisitions, or when demand increases, or barriers to entry are particularly strong.

These scenarios increase observed measures of Q because, in some cases, they pick up the potential for higher rents on assets in place. Our results strongly support these channels.

Regarding firms with product portfolios in decline, we find that they are significantly more likely to be targets of acquisitions. Because selling assets can generate return premia, asset transfer to more youthful growing firms can serve as a primary way declining firms can earn rents for their shareholders. In contrast, when declining firms experience rising market values, we find that these firms switch from selling assets to buying assets (they become acquirers rather than targets), consistent with these firms making risky bets in an attempt to transition to more youthful stages of the life cycle. Our results regarding life cycle transitions support this intuition as firms in decline with high Q are indeed likely to transition to earlier and more youthful stages of the life cycle.

These unique investment and acquisition patterns are not possible to observe using simple life cycle proxies such as firm age, as they contain inadequate dimensionality to observe the rich distribution of growth opportunities across firms in different life cycle stages. Moreover, the informativeness of firm age is limited by the fact that life cycle transitions are not deterministic and shocks can also accelerate the aging process, and in some cases, firms can transition back toward more youthful states. Investment patterns associated with life cycle stages thus do not progress linearly, as new strategic choices emerge later that were not focal for younger firms, and these same choices can then later become non-focal again in late stages of the cycle.

Our approach is based on text analysis of 10-Ks using the anchor-phrase methods used in existing studies such as Hoberg and Maksimovic (2015) and Hoberg and Moon (2017). This approach entails the construction of elaborate textual search queries that require words from 2-3 word lists to appear in close proximity in the text. Simpler methods such as simple word lists are less useful for this purpose because the economic concepts associated with life cycles are often multidimensional in how they are expressed in text, and simple word lists do not require the necessary vocabulary to appear in close proximity. We view 10-Ks as a nearly ideal laboratory for this purpose because all public firms must file 10-Ks annually, and they must be up to date and reflective of current firm activities. Regulation S-K also requires firms to disclose information about innovation spending and their product portfolios.

We validate our life cycle model by looking at the relationship between our variables and firm age and also to changes in the firm's product portfolio. The results provide strong validation. We find that, even after including firm fixed effects, both product and process innovation occur earlier in a firm's life. Maturity, decline, and ultimate delisting occur later. We also find that the size of the firm's product description in its 10-K is growing when the firm is in the product innovation stage of the life cycle, and that it is shrinking when the firm is in the declining stage. This same variable is not strongly related to process innovation or maturity. These results are strongly consistent with the predictions of the product life cycle theory in Abernathy and Utterback (1978). We also observe very sensible transition patterns, as earlier stage firms such as those in the product innovation stage are likely to later transition to later stages such as maturity over time.

Our results broadly support the aforementioned predictions regarding the link between life cycles and investment, investment sensitivity to Tobins' Q, mergers and acquisitions, and outcomes. Firms in the product innovation stage invest heavily in R&D, and they invest even more intensively when their market valuations rise. In contrast, firms focused on process innovation and more mature firms invest heavily in CAPX, and their CAPX is also more sensitive to rises in Q. Firms in the mature and declining stages of the cycle have greater sensitivity of acquisitions to Tobins' Q, consistent with these firms having exhausted their internal growth options and relying instead on external options. Also notable is that firms in some life cycle stages have negative sensitivity to Tobins Q for various investment policies. This is due to the fact that such firms are focused on other of the investment policies given their position in the cycle. These results help to explain the decline in CAPX investment sensitivity to Tobins Q reported by existing studies (see Gutierrez and Phillipon (2016) for example).

Regarding mergers and acquisitions, our results most strongly indicate that more mature firms, particularly those in decline, are more likely to be targets and sell their assets. In contrast, firms that are earlier in the life cycle, and who have internal growth options, tend to be the acquirers. Hence there is a broad pattern of asset transfer from firms who are in the later stages of the cycle to firms that are in the more youthful stages. This is consistent with more elderly firms delivering value to their shareholders by selling assets to more youthful firms, who have the capacity to pay merger premia for target assets.

Firms that are later in the life cycle, maturity and decline, tend to have higher current profits. Firms that are earlier in the cycle, in contrast, have lower current profits but higher sales growth. We also observe a higher rate of IPO activity and venture funding activity in markets that are broadly more focused on product innovation. Firms that are later in the cycle are more likely to delist and to sell their assets via M&A. These results suggest that outcomes for firms in the various stages of the cycle are consistent with intuition.

Finally, we find that massive shocks can result in firms making dramatic transitions in the life cycle. Following the technology bust of 2000 to 2002, we find that firms in the more innovative stages transition 1-2 steps in the cycle. Firms doing product innovation transition to maturity, and in some cases, delisting. Firms doing process innovation ex ante transition to maturity, decline, and delisting. We find similar patterns for the financial crisis period. Again, firms make dramatic transitions from more early stages to later stages of the cycle. These results suggest that there are potentially important and long term consequences of major shocks that can impair the innovative position that some firms have ex ante and shift these firms toward a static and more mature, or even declining, position in the marketplace.

Overall, our results suggest that understanding a firm's position in the life cycle can have far reaching implications for its corporate finance policies and its longer term outcomes. These tests also reveal important ramifications for innovation and the competitiveness of various product markets.

2 Literature Review

Creating value in a product market requires going through a set of predictable stages that, such that in each stage, the relation between Q and different types of investment will change. Consider for example a new manufacturer of a commercial airliner. Initially, the firm will focus on design and development. Over time, the firm will also invest in plant and production line efficiency. Once those are created, much of the firm's value will come from managing the sales and production processes in a continuous and stable fashion. Finally, as new competitors arise, the focus will be on winding up production while supporting the products sill in service. Each of those stages creates value, but will require different skills. They will also entail different relations between investment in development, sales, and physical plant. In some stages, the relation between optimal investment in a particular category of assets and Q may be negative.

Our analysis of the relation between Q and investment builds directly on Abernathy and Utterback's (1978) model of stages of the product life-cycle. They argue that projects traverse a set of stages: (1) product innovation, (2) process innovation, (3) stability and maturity, and finally (4) product discontinuation. In our analysis, we take these stages at the individual project level as given, but argue that a firm is a portfolio of projects, potentially at different stages. As hypothesized by Klepper (1996), and Klepper and Thompson (2006), industries consist of submarkets, to which the firm can enter. We posit that participation in each submarket can be viewed as relatively distinct projects that each cycle through the Abernathy and Utterback stages. Each stage lasts a limited amount of time. As a result, the relation between market value and the types of investment in each sub-market varies over time, as posited by Abernathy and Utterback (1978), but at any one time, the firm may be in a different stage in product cycle for each submarket.

Because the firm may be at different stages in each of its projects, we do not classify the firm as a whole as being in a particular stage, but we measure each component separately. Over time each of the components may increase or decrease in response to competition and shocks, or to the firm's comparative advantage and entry and exit from sub-markets. We use text analysis to provide metrics of each firm's product portfolio weights on each Abernathy and Utterback stage in the life cycle.

Our paper is consistent with the broad approach of Jovanovic (1982), who argues that young firms start off with unknown ability to exploit growth opportunities. Thus the investment and financing decisions of firms at the beginning differ from those of other firms. Much of subsequent theory has examined these differences and their implications for firms of different ages through the prism of information — either asymmetries of information, or of mutual learning about the firm's potential by its management and its investors over time. We argue that the evolution of the firm involves more than the unfolding of information about the firm over time, but also the transition through a series of states.

Our paper is also related to the recent work on the relation between firm age and firm performance. Loderer, Stulz and Waelchli (2016) argue that as they age firms become more rigid and less able to optimally respond to growth opportunities. In their analysis product market competition slows down this process, whereas financial market monitoring speeds up aging as if forces firms to focus on their relationships with investors. Our metrics quantify the extent to which firms are engaged in developing product market opportunities and managing their current assets. Thus we are able to link the firm's exploitation of growth opportunities and management of assets directly to investment choices and the effects of those on performance.

Much of the empirical analysis analyzing firm investment decisions is based on the Q-theory of investment, worked out by Hayashi (1982) and Ericson and Whited (2012). This theory predicts that the firm's investment opportunities can can be measured by the ratio of the firm's market value to that of the firm's assets.[1] Given adequate homogeneity between firms and assumptions about competition in the market for outputs and inputs, it is straightforward to derive the usual relations between investment and Q. A maintained assumption in the Q-theory of investment, derived from a neoclassical model, is that there exists a positive relation between the expected value of future cash flows realized by the firm and its capital stock. However, the relation between Q and any particular capital asset is more complex in practice. Thus, it is understood that an R&D firm may have a high market value but may not purchase production facilities before it has a product (or even afterwards if the firm outsources production), and that a mature firm can increase its market valuation, and hence its Q, by shuttering or selling off inefficient operations. This is understood, but does not affect the workhorse model because of the difficulty of quantifying these cases. Our paper provides an empirical framework for identifying and quantifying these effects for firms using their regulatory mandated disclosures.

Our paper is also related to the recent literature on the changing relation between Q and investment, which finds a breakdown of the relation between industry Q and capital investment, Lee, Shin and Stulz (2016) show that since the early years of this century, capital no longer flows into high Q industries, and in fact flows out. It is likely that this change is related to the large drop in the number of firms in public markets and the decline in IPO activity. The drop in levels of expenditure on capital has also been extensively documented and explored by Gutierrez and Philippon (2016).

Building on work by Grullon, Larkin, and Michaely (2016), Mongey (2016), and Bronnenberg et al. (2012), which have shown increases in concentration in U.S. industries over time, and increases in price-cost mark-ups (Nekarda and Ramey 2013), Gutierrez and Philippon (2017) argue that the relation between capital expenditures

[1] See Peters and Taylor (2015) for how to incorporate intangible capital, and Hassett and Hubbard (1997), Caballero (1999) and Philippon (2009) for reviews of the literature.

might have broken down because of the increases in market power across a range of industries. Thus, to the extent that market power is maintained by restricting output, its rise should be associated a rise in Tobin's Q across industries and a drop in investment.[2] Our approach differs in that we quantify the effort the firm directs to each of the life cycle stages identified by Abernathy and Utteback on the relation between investment and the market's valuation of the firm. Using our framework, we can directly measure the relation between life cycle stages, valuation, investment, acquisitions and competitive shocks that the firm receives.

Our paper is also related to the recent literature arguing more broadly that, driven by competitive shocks and technological change, US firms have changed considerably in the last twenty years. Hoberg and Moon (2017) analyze the increase in outsourcing by firms. Rajan and Wulf (2006) and Gudaloupe and Wulf (2007) show that competitive pressure also affects the firm's firm's organizational structure, reporting relationships, and tendency to engage in R&D (see Autor et al 2016).[3] Using Census data, Magyari (2017) shows that US firms exposed to Chinese import competition shift resources into R&D and service production . More broadly, there is evidence that recent increase in inequality between firms that is manifest in differences in productivity, rates of return and labor compensation (Bloom (2017), Frick (2016)). We are able to quantify how these pressures will affect the activities of different subpopulations of firms.

3 Data and Methods

The new life cycle variables we create derive purely from 10-K text. All of the text-extraction steps outlined in this paper can be programmed using familiar languages and web-crawling techniques. For convenience, we utilize text processing software provided by metaHeuristica LLC. The advantage of doing so from a research per-

[2]Note that while this argument is intuitive, it is not obvious. To the extent that extra capacity is required to punish deviations from a collusive equilibrium, excess capacity might still be required as discussed by Kreps and Fudenberg (1986) and Maksimovic (1988).

[3]For an analysis of the effect of trade competition on European firms, see Bloom, Draca and Van Reenen (2016).

spective is that the technology contains pre-built modules for fast and highly flexible querying, while producing output that is easy to interpret.[4] For example, many of the variables used in this study are constructed by simply identifying which firm-year filings (within a set of 77,547+ filings) specifically contain a statement indicating the state of maturity of its product portfolio.

3.1 Data

Our sample begins with the universe of Compustat firm-years with adequate data available between 1997 and 2015. We restrict the sample years based on availability of SEC Edgar data. After limiting the sample to firm-years that are in Compustat, have machine readable 10-Ks (both current year and lagged), have non-missing data on operating income and Tobins Q, have sales of at least $1 million and assets of at least $1 million, we are left with 77,547 firm-years. Our sample of 10-Ks is extracted by metaHeuristica by web-crawling the Edgar database for all filings that appear as "10-K," "10-K405," "10-KSB," or "10-KSB40." The document is scanned for text pertaining to life cycles, fiscal year, filing date, and the central index key (CIK). We link each 10-K document to the CRSP/COMPUSTAT database using the central index key (CIK), and the mapping table provided in the WRDS SEC Analytics package.

3.2 The Product Life Cycle

Our goal is to use direct textual queries that are highly specific to identify the life cycle state of a firm's product portfolio. This "anchor-phrase" method of textual querying has been used in past studies including Hoberg and Maksimovic (2015) and Hoberg and Moon (2017).

Given motivations from the literature, we propose a product portfolio life cycle with five states: (1) product innovation, (2) process innovation, (3) stability and

[4] For interested readers, the software implementation employs "Chained Context Discovery" (See Cimiano (2010) for details). The database supports advanced querying including contextual searches, proximity searching, multi-variant phrase queries, and clustering.

maturity, (4) product discontinuation, and (5) delisting. A necessary condition for success is that firms discuss these states in their 10-K, and that the content describing the product portfolio can be measured using text analytic techniques. Regarding the existence of content, we point readers to Regulation S-K, which requires that firms disclose details relevant to identifying these states. Item 101 of Regulation S-K for example requires that firms provide "An explanation of material product research and development to be performed during the period covered" by the 10-K. A substantial amount of text explaining product development activities would indicate that the firm is in the earliest of the life cycle stages (product innovation).

Regarding process innovation, the same disclosure rules require the firm to disclose its results from operations, of which the costs of production are a significant component. A firm that is focused on process innovation is expected to devote considerable text, particularly in MD&A to its activities and efforts to reduce costs. A firm in the third state, stability and maturity, should be characterized by discussions focused on continuation and market shares, but without references to product innovation or process innovation. Finally, a firm in the fourth state will indicate its activities of product discontinuation.

For parsimony and to reduce labeling clutter, we will refer to each of the above five states as Life1, Life2, Life3, Life4, and LifeDelist, respectively. The final state of delisting is an absorbing state. Because the other four states are consistent with continued operations, we intend to build a depiction of a continuing firm's product portfolio as a four element vector {Life1, Life2, Life3, Life4} such that each of the four elements are bounded in [0,1] and the sum of the four components is unity. Indeed we fully expect firms to participate in more than one of these activities in any given year, and the relative intensities of each activity indicate's the firm's position in the cycle. For example, a firm with a vector {.6,.3,.1,0} would be seen as earlier in the life cycle than a firm with weights {.1,.3,.3,.3}.

To measure the firm's loading on the first stage of the product life cycle, "Life1", representing product innovation, we identify all paragraphs in a firm's 10-K that contain at least one word from each of the following two lists (an "and" condition, not an "or" condition).

Life1 List A: product OR products OR service OR services

Life1 List B: development OR launch OR launches OR introduce OR introduction OR introductions OR new OR introducing OR innovation OR innovations OR expansion OR expanding OR expand

To measure the firm's loading on the second stage of the product life cycle, "Life2", representing process innovation, we identify all paragraphs in a firm's 10-K that contain at least one word from each of the following two lists.

Life2 List A: ORcost OR costs OR expense OR expenses

Life2 List B: labor OR employee OR employees OR wage OR wages OR salary OR salaries OR inventories OR inventory OR warehouse OR warehouses OR warehousing OR transportation OR shipping OR freight OR materials OR overhead OR administrative OR manufacturing OR manufacture OR production OR equipment OR facilities OR facility

To measure the firm's loading on the third stage of the product life cycle, "Life3", representing maturity and stability, we require three word lists.

Life3 List A: product OR products OR service OR services

Life3 List B: line OR lines OR offerings OR mix OR existing OR portfolio OR current OR categories OR category OR continue OR group OR groups OR customer OR customers OR core OR consists OR continue OR provide OR providing OR provided OR provider OR providers OR includes OR continued OR consist

Life3 List C (exclusions): development OR launch OR launches OR introduce OR introduction OR introductions OR new OR introducing OR innovation OR innovations OR expansion OR expanding OR expand OR future OR obsolete OR obsolescence OR discontinued OR discontinue OR discontinuance OR discontinuation OR discontinues OR discontinuing OR cost OR costs AND expense OR expenses

To measure Life3, we identify all paragraphs in a firm's 10-K that contain at least one word from each of the first two lists above (List A and List B above), and that do not contain any of the words from the third list (List C). Paragraphs satisfying these conditions indicate discussions of the firm's products and its offerings that explicitly do not mention any of the activities associated with the other three operating stages of the cyle (Life1, Life2, Life4). In particular, Life3 List C above is the union of the list of defining terms associated with each of the other life cycle stages.

To measure the firm's loading on the fourth stage of the product life cycle, "Life4", representing product discontinuation, we identify all paragraphs in a firm's 10-K that contain at least one word from each of the following two lists.

Life4 List A: product OR products OR service OR services OR inventory OR inventories OR operation OR operations
Life4 List B: obsolete OR obsolescence OR discontinued OR discontinue OR discontinuance OR discontinuation OR discontinues OR discontinuing

To measure the final 5th stage, "LifeDelist", we identify delistings that are specifically due to poor performance. We use the CRSP delisting codes in the interval 520 to 599, which indicate delisting due to poor performance, and not due to mergers and acquisitions.

Based on the above queries, the end result is a count of the number of paragraphs that hit on the given word lists for Life1 to Life4. The final absorbing state LifeDelist is a dummy equal to one if the firm delists. Because the first four states are consistent with continued operations, we wish to tag operating firms regarding how much of each state their overall product portfolios is exposed to. Hence, we divide each of these four paragraph counts by the total paragraph counts of the four. The result is a four element vector for each operating firm that sums to one $\{Life1, Life2, Life3, Life4\}$ with $(Life1 + Life2 + Life3 + Life4 = 1)$. All four variables are also non-negative and cannot exceed unity.

We also gather information on the size of each firm's 10-K as we seek to control for document length in our regression analysis. Our measure of length is the natural logarithm of the number of paragraphs in the given firm's 10-K as identified by the metaHeuristica system. We refer to this control variable as "Whole 10-K Size". Our results are not highly sensitive to whether this control variable is included or not included in our regression analysis.

3.3 Policy and Outcome Variables

We examine two investment policies R&D/assets, CAPX/assets, and we also examine the decision to acquire assets or to sell assets as a target. The R&D and CAPX variables are constructed directly from COMPUSTAT data with total assets (AT) being the denominator. When R&D (XRD) is missing, we assume it to be zero. All variables constructed as accounting ratios are winsorized within each year at the 1%/99/

We also examine a number of real outcome variables to assess how ex-ante life cycle conditions relate to ex post outcomes. We focus on operating income/assets, operating income/sales, log sales growth, and various measures of IPO and VC funding activity occurring in a given firm's industry. We compute the IPO-rate for SIC-3 industries as the number of IPOs in a given SIC-3 industry divided by the number of publicly traded firms. Analogously, we compute the IPO-rate for TNIC-3 industries (see Hoberg and Phillips (2016)) as the number of firms in a TNIC industry that are IPO firms divided by the number of firms in the TNIC industry. Finally, we measure each firm's text-based similarity to firms conducting IPOs or receiving VC financing following Hoberg, Phillips, and Prabhala (2014). In particular, this is equal to the cosine similarity between a firm's 10-K business description and the business descriptions of IPO or VC firms in the same year from SDC Platinum. These variables indicate whether IPO or firms receiving VC funding are entering in product markets that are particularly proximate to a given firm.

3.4 Summary Statistics and Correlations

Table 1 displays summary statistics for our 1997 to 2009 panel of 77,547 firm-year observations. Panel A reports statistics for our new life cycle variables. We first note that the values of Life1 to Life4 sum to unity, which is by construction. The table also shows that textual prevalence is highest for process innovation (Life2), followed closely by maturity (Life3) and product innovation (Life1). However, discussions of product decline are far less common and make up just 4.8% of the total text devoted to all four stages. We also note that the delisting rate (due to poor performance only) is 1.6% in our sample.

[**Insert Table 1 Here**]

Investment rates are also consistent with existing studies. The average firm spends 4.6% of its assets on R&D, and 4.5% of its assets on CAPX. Roughly 34% of firms participate in acquisitions (partial or full), and 12.1% of firms acquire a target firm in full (both acquisition variables include both public and private targets). Analogously, 18.5% of firms sell at least some assets, and 4.7% are full firm targets. The average Tobins Q in our sample is 1.57.

Regarding outcome variables, the average firm in our sample has a profitability ratio of 8.5% relative to sales and 4.9% relative to assets. The average log sales growth is 9.8% and the average IPO rate for firms in our sample is 2.8% based on TNIC-3 industries and 1.7% based on SIC-3 industries.

Table 2 reports Pearson correlation coefficients for our main variables of interest. As should be the case because they sum to unity, the Life1 to Life4 variables are negatively correlated with one another. However, the degrees of correlation echo some patterns we will reinforce later. One is that the product innovation stage Life1 is more related to the mature firm stage Life3 than it is to process innovation Life2. This result echoes changes in the economy favoring service-oriented firms. An extreme example is software firms, which need little in the way of process innovation once their product is itself is developed, as production and distribution costs for software are generally small as for example compared to manufacturing firms. For this reason, we present most of our results both for the overall sample, and then separately for manufacturing firms.

[Insert Table 2 Here]

We also observe that Life1 is most negatively associated with firm age (-18.3%) and Life4 is most positively associated with firm age (17.4%). This corroborates a primary prediction of the product life cycle theory. Firms generally begin life in a mode where a large fraction of their product portfolio is in a product innovation stage. In contrast, firms end life in a state of product discontinuation and eventual delisting. However, one perhaps surprising result in Table 2 is that process innovation (Life2) seems to come later as firms age than does maturity (Life3). We note that this univariate correlation reflects across-firm variation and not within-firm variation and thus is related to cohort effects. For example, manufacturing firms, which are often process focused, went public earlier in the United States relative to many service-oriented firms who generally have mature product offerings such as UPS. In particular, we will show in the next section that the ordering of Life2 and Life3 reverses to the ordering predicted by the product life cycle once we include firm fixed effects. Hence at the firm level, process innovation does in fact precede maturity on average.

Another interesting finding is that the table also echoes one of our main results, which we rigorously establish later. Regarding investment and M&A, we observe that firms in different stages of the life cycle have very different growth options. Life1 firms focus heavily on R&D (51.5% correlation), and Life2 firms focus on CAPX (33% correlation. As we would expect given they are mature and presumably lack internal growth options, Life3 firms correlate negatively with both forms of investment. Morever, Life3 firms have almost exactly zero correlation with sales growth, further affirming the appropriateness of interpreting this state as maturity.

One additional result is that acquisitions are positively associated with Life3, indicating that mature firms consider acquisition-based growth options in the life cycle when their internal growth options are exhausted. Life4 firms, in contrast, are negatively correlated with all three forms of investment (R&D, CAPX, acquisitions) and instead are positively correlated with being targets of acquisitions. Hence, the option to transfer assets to growing firms is one way that declining firms can create value for their shareholders even in the presence of discontinuation. Although these findings are univariate and purely associative, we will show that many of these relationships will hold up to more rigorous regression models with firm fixed effects.

Figure 1 illustrates how Life1 to Life4 vary over our sample period for the quartiles of smallest and largest firms in our sample (based on total assets), sorted annually. We expect these measures to vary cross-sectionally for firms of different size because smaller firms in our sample are likely to be either young firms focused on launching their product in a narrow range of markets, or older firms that have not been able to expand successfully outside a narrow area of competence. In contrast, large firms are likely to be engaged in multiple activities across several markets and may exhibit different portfolio mixtures of Life1 to Life4. In addition, firms of different sizes might be differentially impacted by major product market shocks.

[**Insert Figure 1 Here**]

As expected Figure 1 shows that small firms have higher values of Life1 than large firms. However, it is noteworthy that following the 2008 financial crisis large firms materially narrow the gap between their level of Life 1 and that of small firms. This suggests that, in this period, large firms are becoming significantly more entrepreneurial. Also as expected, large firms have higher values of Life2 than small firms. The level of Life2 is generally rising over our sample period, indicating that firms are devoting more effort to process innovation over time.

Figure 1 also shows that the level of Life3 is initially much higher for large firms than for small firms, but that large firms experience substantial decline in Life3 levels over time. By the end of the period, the gap between the large and small firms has essentially closed. Together with the increase in Life1 over time, our findings for Life3 indicate that large firms are undergoing a transition during our sample period.

Values of Life4 increase for all firms around the time of the technology bust, during the period 2000-2004. Life4 levels then stay at this elevated level through the remainder of our sample period. During this period, the number of firms in our sample declines from 5830 to 4880 as many firms delist. The concurrent increase in Life4 and delisting rates are consistent with a hightened level of restructuring and failure by firms during this period.

Our finding that firms shift away from Life3 (which is a state that is stable and relatively inactive), and toward the other stages of the cycle (which are active and require investments and changes in product offerings) is consistent with large firms transitioning from relatively static life cycle strategies to dynamic strategies. These dynamic strategies cover Life1, Life2, and Life4, and thus entail continuous refinement of product portfolios, and these firms have a relatively integrated presence across multiple life cycle stages.

We summarize this first-order shift of larger firms toward a more dynamic firm over our sample period by combining the four Life measures into firm dynamism index:

$$DynamismIndex = Log[\frac{Life1 + Life2 + Life4}{Life3}]. \tag{1}$$

Here we take Life3 to be a mature and relatively inactive state, and the other Life measures as being associated with product and process development and restructuring of operations (dynamic strategies). In Figure 2, we show how this dynamism index changes over time for both small and large firms. At the beginning of the period, small firms are more dynamic than large firms. However, over time, small firms become more dynamic, but larger firms become dynamic at a much higher rate. Overall, larger firms experience a 68% growth in dynamism compared to just 20% for smaller firms. By the end of our sample period, large firms have substantially reduced the gap between themselves and smaller firms. Thus, by our measures, large firms have undergone a major transformation, especially following the 2008 crisis and recession.

[**Insert Figure 2 Here**]

In Table 3, we further consider the results in Figure 2. Our goal is to examine if the rise of the dynamic firm is related to measures of market power and globalization. In particular, we sort firm-years into terciles based on firm size (logassets) and also by the dynamism index (defined above). We then report the average values of measures of market power (total similarity and product market fluidity) and measures of globalization (measures of offshore sales and offshore purchase of inputs from Hoberg and Moon (2017)).

[**Insert Table 3 Here**]

Panels A and B of Table 3 show that as we move from low dynamism to high dynamism firms, both measures of market power become considerably stronger when we focus on larger firms in the third row. In particular, total similarity declines from 19.7 to 6.6, indicating significantly stronger product differentiation. Profitability (OI/assets) moves from 7.9% to 11.5%. Both findings are consistent with significant increases in market power. In contrast, when we consider smaller firms in the first row, the results go in the other direction. The results are thus consistent with the rise of the dynamic firm being consistent with greater market power, but only for larger firms, likely because smaller firms do not have the depth of resources to implement this more complex strategy successfully.

Panels C and D of Table 3 show that increases in dynamism are also highly correlated with increases in globalization, both on the output side and the input side of the firm. Both the mentions of selling goods abroad, and buying inputs abroad, from Hoberg and Moon (2017) are higher for larger firms when they are more dynamic. The increases are economically large as mention of outputs rises from .036 to .061. Mentions of purchasing inputs abroad more than doubles from .027 to .065. This is consistent with dynamic firms being more flexible and producing more product overseas, consistent with some focus on process cost improvements in Life2. In contrast to the large firm results, both globalization variables increase far less for smaller firms.

The differential response of large versus small firms to increased dynamism are highly statistically significant both for the market power and offshoring variables. The results are consistent with dynamism being associated with increased market power and globalization (but only for larger firms). This also is consistent with the hypothesis that dynamism is an optimal strategy in the presence of increased globalization as firms compete with foreign multinationals on many margins. Integration along all states in the product life cycle can thus offer superior protection from potential entrants as even innovative entrants would then need to out-innovate these deep pocketed incumbents who also have a focus on Life1.

4 Validation and Life Cycle Transitions

4.1 Validation

Our life cycle measures are derived using very direct textual queries, and hence their interpretation is fairly well established through texture. Yet, we feel it is important to stress test this interpretation of our variables by running two validation tests. These tests are intended not only to corroborate the life cycle interpretation, but also to examine the economic magnitude of the economic links of these variables to quantities theory would suggest they should strongly relate to.

Our first test is to examine whether the product life cycle, as originally proposed by Abernathy and Utterback (1978), can be illustrated using our measures. The central prediction is that product innovation (Life1) should precede process innovation (Life2), which in turn should precede maturity (Life3), decline (Life4) and ultimate delisting. To test these predictions, we regress each life cycle variable on firm age, and look at models with and without other basic controls such as firm size and Tobins Q. We note that it is particularly important to include firm fixed effects in these tests, as only then can we draw conclusions regarding whether individual firms specifically make transitions consistent with this predicted cycle. For completeness, we also include year fixed effects and a control for document length, and we cluster standard errors by firm. The results are presented in Table 4.

[**Insert Table 4 Here**]

Examining the sign and the coefficients for the log age variable in Panel A yields support for the Abernathy and Utterback (1978) life cycle. In particular, the table includes both firm and year fixed effects, and we observe that Life1 and Life2 are negatively associated with firm age, whereas Life3, Life4, and Life Delist are positively associated. This is direct within-firm evidence that product and process innovation are a mainstay for younger firms. Over time, firms transition to stability, and then ultimately decline. Our inferences are little-changed when we add the additional control variables in Panel B.

The only unexpected finding in Table 4 is that the coefficient for Life2 is more negative than the coefficient for Life1. However, we note that the difference between the two is not significant in Panel B. Yet one implication is that many very young firms are, in fact, very concerned with process innovation and in cutting costs. This for example could be consistent with innovative firms needing to focus on at least some cost cutting due to the presence of financial constraints. Hoberg and Maksimovic (2015) show that these younger and more innovative firms indeed appear to suffer more from financial constraints than do any other firm types.

Our second validation test is to examine if our life cycle measures, particularly Life1 (product innovation) and Life4 (product differentiation) indeed predict changes in the size of the firm's product portfolio. Our first dependent variable of interest is thus the logarithmic growth in the size of the 10-K business description from one year to the next, which has been used previously in Hoberg and Phillips (2010). Our predictions for validation is that Life1 should positively associate with product description growth and Life4 should be negatively associated. We thus consider regressions where product description growth is the dependent variable, and we include firm fixed effects plus additional controls.

The results are reported in Table 5. We note that because the four variables (Life1 to Life4) sum to unity, we cannot include all four in the regression model as they are co-linear with the intercept. Hence we use Life3 as the hold-out stage of the cycle, and the coefficients on the remaining life cycle variables should be interpreted as whether the given dependent variable is more or less relative to Life3 firms. Because Life3 is a stage of maturity and stability with fewer predicted investments, we believe it is the most intuitive reference group.

[**Insert Table 5 Here**]

Panel A reports results when product description growth is the dependent variable. The table shows that product description sections of the 10-K grow significantly faster when the firm is in the product innovation stage (Life1), and growth is significantly more negative when the firm is in the product decline stage Life4. The results are highly significant at well beyond the 1% level despite the inclusion of controls such as firm age and the use of firm fixed effects. This provides strong validation of our key life cycle variables. Also relevant, we do not see significant results for Life2 or Life3, as there are not strong predictions for product offerings to increase or decrease when the firm is engaged in process innovation or is mature and stable.

We also examine the link to Tobins Q in rows (2) and (3). Row (2) shows as expected that firms with higher Q experience stronger product description growth. In Row (3), we examine if firms in each stage of the life cycle react to Q differentially. We again note that Life1 to Life4 sum to unity, so by replacing the level of Tobin Q in Row (2) with the four cross terms, we essentially are estimating four distinct conditional effects of Q for each stage of the life cycle, which forms a full partition of total life cycle weights. The results in Row (3) show that the positive link between Q and product description growth is primarily attributable to Life1 firms, who therefore experience ultra-fast growth when their Q is additionally high. Life3 also have some sensitivity to Q, but less than Life1. Life2 and Life4 have no sensitivity. We will illustrate later that this is likely because Life2 firms and Life4 firms have different growth options and for example high Q predicts increased capital expenditure and investment in process rather than product, or increase M&A activity.

As an additional test of validation, Panel B of Table 5 reports results when the dependent variable is product market fluidity instead of product description growth. Product market fluidity measures the extent to which product vocabulary is rapidly turning over from year to year in the firm's local industry. For example, a high fluidity would indicate that product innovation is moving at a particularly rapid pace as would be required to generate massive changes in product portfolios year-to-year. Fluidity is discussed in Hoberg, Phillips and Prabhala (2014) and is a broader measure of product market flux and competitive threat than is the narrower concept of product description growth.

The results in Panel B echo those in Panel A. However, product market fluidity is only significant for Life1 exposures, particularly when the firm has a high Tobins Q. Because product innovation is uniquely a state of affairs for Life1 firms, we find these results to be particularly compelling as the most rigid prediction is that product innovation should be high when a firm is exposed to Life1, but is near zero in all other life cycle states.

Overall, we view the evidence in this section as strongly validating the interpretation of our Life1 to Life4 variables as valid measures of the product life cycle as depicted in the literature including Abernathy and Utterback (1978). Particularly when coupled with the fact that we use highly specialized textual searches for life cycle content, that are intended to maximize interpretability of search hits, we believe these measures are both intuitive and consistent.

4.2 Life Cycle Transitions

We next examine transition intensities across states in the life cycle. To do so, we consider regressions where the dependent variable is one of the five life cycle variables (includes Life Delist), and the RHS variables include the ex-ante life cycle variables of the given firm including controls. Importantly, for each life cycle variable, the RHS variables additionally include the lagged value of the dependent variable itself. Hence we are also able to assess independently how sticky each state is. Because we include the lagged dependent variable, we do not include firm fixed effects due to redundancy, however we do include year fixed effects and we cluster standard errors by firm. This model provides maximum interpretation as we are able to observe flows across life cycle states as well as persistence of each state.

The results are displayed in Table 6. In Panel A, we consider a baseline panel with just the four life cycle variables as RHS variables plus basic controls including age, size, and document length. Then we consider a second set of tests in Panel B where we add cross terms with Tobins Q. This allows us to examine if life cycle transitions accelerate or go in different directions when firms have high Tobins Q.

[**Insert Table 6 Here**]

Panel A of Table 6 shows that all four life cycle stages are quite sticky, particularly Life1 to Life3. These stages are all roughly 80% persistent (Life2 being most persistent at 85%) and hence firms can remain in these stages for many years. However, we note that Life4 is just 52.8% persistent, and hence firms in decline tend to resolve their situations rather quickly. Overall our results in Panel A indicate that, not surprisingly, these firms are significantly more likely to delist due to poor performance.

Perhaps more surprisingly, they are also more likely to transition to a state of stability (Life3) or to process innovation and cost cutting (Life2). This suggests that firms entering decline tend to discontinue products that have too little demand, and they tend to take on more risk in an attempt to return to a state of efficient production with more stable markets. However, this practice entails material risk as we observe that many firms end up delisting. Also noteworthy is that these firms are significantly less likely to transition to product innovation (Life1) as their state of aging in the life cycle likely makes such a transition too difficult for both corporate culture and economic reasons.

The table also shows that firms engaged in product innovation often transition directly to Life3 and hence they skip Life2. This is consistent with the idea that for service-oriented firms, which make up a large fraction of our sample, production is less important as many products such as software or medical services can be delivered without major investments in industrial production. For this reason, we report separate results for manufacturing firms later in this sample and the results will confirm this interpretation.

Panel B of Table 6 illustrates that firms with high Tobins Q experience significantly modified transition probabilities. Not surprisingly, firms focused on product innovation (Life1) more persistently remain in this youthful state longer when their Tobins Q is high. This is consistent with these firms having particularly good growth options relating to product innovation, and more time is needed before they are fully exercised. Similarly, process innovation firms (Life2) with higher Q also remain in this state of process innovation longer when Q is high. This is consistent with these firms having particularly good growth options relating to improving their production and reducing costs, and hence more time is also needed here as well. Both Life1 and Life2 firms are also significantly less likely to transition to more mature states when their Q is high. For example, both are less likely to transition to Life3, and the Life2 firms are also less likely to enter decline (Life 4) and delisting.

In contrast, we do not see significant changes in transitions for Life3 firms when their Q is high. For these firms, whose value is mostly weighted on assets in place, a high market value likely indicates the existence of greater profitability and protection from rivals, and Q is less likely to be a valid measure of investment opportunities. This is directly implied by the interpretation of Life3 as a state of maturity and stability. Finally, we observe only weak results for Life4 firms indicating a slightly elevated likelihood of transitioning to Life1 when their Q is high. Our later results will suggest that higher Tobins Q for both Life3 and Life4 firms is also associated with investment growth options in the form of acquisitions, consistent with firms in both stages lacking organic investment opportunities.

Because many of the firms in our sample are service oriented and likely focus little on process innovation, we re-run the transition analysis separately for manufacturing firms in Table 7. All specifications are the same, except the sample is now limited only to firms having SIC codes in the range 2000 to 3999.

[**Insert Table 7 Here**]

Comparing Table 7 to Table 6 indicates that manufacturing firms generally experience transitions that are quite similar to those for the full sample. However, there are some important differences, particularly relating to process innovation and its interaction with the others states. The main result is in Panel B where we observe a strong reversal for Life1 and Life2 firms when their Tobins Q is high. Whereas these states become more sticky for the overall sample when Q is high, we find that manufacturing firms are more likely to move between Life1 and Life2 when they have high Q. For example, a firm with high levels of product innovation is likely to increase its exposure to process innovation in the next year when its Q is high. Analogously, a firm that is heavily weighted in process innovation is more likely to increase its product innovation in the next year.

For manufacturing firms, unlike for some service oriented firms, both product and process innovation play a strong role in how these firms evolve. The results in Table 7 suggest that these forms of innovation are perhaps quite complementary. In particular, a higher market value indicates transitions toward having more of both. In contrast, for the full sample, a higher Q indicates more polarization and focus on one type of innovation.

5 Investment, Acquisitions, and Outcomes

5.1 Basic Q-investment Regressions

We first examine the cross sectional relationship between investment and Tobins' Q and how that relationship varies across three different types of investment (CAPX, R&D, and acquisitions) for different stages of the life cycle. We also examine how these relationships vary over time following Gutierrez and Phillipon (2016), who documents a major decline in the relationship between CAPX and Tobins Q in recent years.

Following Gutierrez and Phillipon (2016), we run annual OLS regressions where the dependent variable is CAPX/assets, and Tobins Q is the key RHS variable. We include controls for firm size and age. Our focus is on how the R^2 of the model varies over time. The results of this initial test are displayed in the first four columns of Table 8. Consistent with Gutierrez and Phillipon (2016), we find that the R^2 peaks early in our sample by 2003 at 3.3% and then sharply declines thereafter to 0.6%.

[**Insert Table 8 Here**]

We next examine if a conditional model of Tobins Q performs differently. In particular, we replace Tobins Q in this regression with four terms equal to Tobins Q multiplied by each of the variables Life1 to Life4. Because the Life1 to Life4 variables sum to one, this can be viewed as a conditional model indicating investment-Q sensitivity for firms in each stage of the life cycle. We also include the life cycle variables themselves as levels with Life3 omitted due to co-linearity with the intercept given the variables sum to one. We note therefore that the remaining Life variables should be interpreted as Q-sensitivity relative to the mature Life3 firm as a benchmark.

The nine columns in the middle of Table 8 display the results for the conditional model. We note that controls for size and age are still included but are not reported to conserve space. The table shows a remarkable contrast with the basic unconditional model in the first four columns. Unlike the basic model, where R^2 is low and in decline, the R^2 for the conditional model is an order of magnitude larger and is increasing during our sample period. This suggests that in recent years, it is increasingly important to condition on the firm's relative position in the life cycle when predicting its investments. These differences in explanatory power of the two specifications are shown in Panel A of Figure 3. The table also shows that CAPX-Q sensitivity is strongest for mature Life3 firms, and also that the level of Life2 process innovation is also important for predicting CAPX.

The final two columns of the table show that the results are very similar if we run these regressions at the SIC-3 industry level instead of at the firm level. This indicates that product life cycles also have a strong signal at the industry level, something that is not surprising given the life cycle theories and their interpretation as being thought of as industry-level phenomena even moreso than firm-level phenomena.

[**Insert Table 9 Here**]

We next run the same analysis but we examine R&D instead of CAPX sensitivity to Tobins Q. The results are displayed in Table 9. Once again the results are quite different between the basic Q-model and the conditional model. Both models have R^2 that is increasing over time, indicating the growing importance of innovation spending, but the conditional model has an R^2 that is roughly twice as large. Panel B in Figure 3 shows the increase in explanatory power of conditional model over time. The individual terms in the conditional model indicate, not surprisingly, that firms in Life1 doing product innovation invest substantially more in R&D, and particularly when their Tobins Q is high.

[**Insert Figure 3 Here**]

Finally, we run the same analysis but we examine the propensity to be an acquirer and its sensitivity to Tobins Q. The main point we make is that there are three primary forms of investment (CAPX, R&D, and M&A) and all three can be sensitive to Q in different ways and for different stages of the life cycle. The results are displayed in Table 10. Although differences in R^2 are less striking, the conditional model yields many novel insights over the basic model. In particular, it is the more mature firms that have a high acquisition responsiveness to Tobins' Q. This is consistent with what we would expect given the life cycle. For the mature firms, the product market should have converged to something close to a dominant design and firms would have fewer internal growth options relating to product and process. Hence the primary form of growth option that Tobins' Q should pick up would be external growth options such as M&A. Also, for these firms, Tobins' Q might simply pick up firms that are very profitable with strong barriers to entry. Results later in this study will confirm that interpretation as well.

[**Insert Table 10 Here**]

Overall we conclude that the relationship between Tobins' Q and investment is very rich, and basic models of Tobins Q miss most of the rich relationship that does occur between various forms of investment and market valuations. Life cycles are critical to understanding these links, and to understanding why the investment-Q relationship is declining over time.

5.2 Within-Firm Panel Data Tests

The models in the previous section were cross sectional in nature. We now examine how individual firms change their investment and M&A investing patterns in time series when they face changes in the life cycle. In particular, we run regressions using our full sample as a panel data, and we include controls for firm fixed effects, time fixed effects, as well as basic controls such as firm age and size. Once again we consider investment policies such as CAPX, R&D and acquisitions as the dependent variable. All standard errors are clustered by firm.

[**Insert Table 11 Here**]

Table 11 displays the results for internal investments CAPX/assets and R&D/assets. The table shows that, even when rigid firm and year fixed effects are included, that firms with higher Life1 (product innovation) invest more in R&D. However, unlike the cross sectional regressions, there is no sensitivity to Tobins Q in the R&D model. This suggests that at the firm level, innovative firms have a plan in place for product innovation and execute that plan to the best of their ability regardless of the market signal.

However, a different story emerges for CAPX. Although Life1 firms also do more CAPX, this form of investment is sensitive to Tobins' Q. Moreover, this sensitivity is particularly strong for Life2 firms and to some extent mature Life3 firms. This suggests that firms investing in process innnovation react quite strongly to increases in market value and invest more in CAPX during these times. Presumably these investments indicate that the potential for significant advances in process innovation might be very high, and recasting production to newer facilities, which requires CAPX, might be more justified.

Table 12 documents the results of similar regressions when acquisition and target dummies are now the key LHS variables. Panel A shows that innovative young Life1 firms are more likely to acquire assets and elder firms in decline (Life4) are least likely to acquire. The second row shows, in fact, that Life4 firms are significantly more likely to sell assets. These results indicate that acquisitions result in transacting assets "up the life cycle" toward younger more innovative firms and away from elder firms that are in decline.

[**Insert Table 12 Here**]

Regarding sensitivity to Q, the next four columns show that more mature firms experience important changes in the acquisition strategies when their Q becomes higher. In particular, Life2, Life3, and Life4 firms all increase their propensity to acquire. The most innovative Life1 firms, in contrast, are less likely to acquire when their Q becomes high. This suggests that a high Q for a firm doing product innovation indicates that its internal growth options are likely particularly good, and hence external investment such as M&A is not likely. However, a high Q for a more mature firm, which likely has fewer internal growth options, indicates a higher relevance of acquisitions as the high Q likely indicates that external growth options are particularly good.

Panel B shows that the results are very similar for firms in the manufacturing sectors as compared to the full sample. Panel C shows similar but somewhat weaker results for complete mergers. As these transactions are less common, the reduced significance is expected. However, the same patterns generally hold and most coefficients are still significant at the 5% level or better. Even if we further restrict the sample to just manufacturing firms as we do in Panel D, the results still remain significance despite the stringent controls for firm fixed effects.

5.3 Outcomes and Life Cycles

Table 13 uses the same panel data settings as do Table 11 and Table 12, but now we consider various outcome variables as the dependent variable. As before, all LHS variables are from year $t+1$ and all RHS variables are measurable in year t.

[Insert Table 13 Here]

The table first shows results for profitability OI/assets and OI/sales. We find that Life1, Life2, and Life4 all have negative coefficients. Because Life3 is the benchmark for comparison given it is the omitted variable (recall that the sum of Life1 to Life4 is unity), this indicates that firms in Life3 are significantly more profitable than any of the other life cycle stages. This is fully consistent with predictions from the life cycle theories, as mature firms have mastered the identification of a dominant design on the product side, and they have already optimized their production processes. These mature firms are thus primarily interested in maximizing profits rather than investing. We also see more confirmation of this hypothesis as Life3 firms are even more profitable when they have high Tobins' Q. This indicates that high Q not only can predict future investments, but it also loads highly on profits and likely stronger barries to entry. Panel B shows that results are similar for manufacturing firms.

Table 13 also shows, not surprisingly, that firms in more innovative stages of the life cycle experience faster sales growth. This is particularly true when firms additionally have high Q, as then firms in all stages of the life cycle experience increased sales growth. Finally, we document that IPOs and funding by venture capitalists is most likely to occur in industries that are dominated by Life1 product innovating firms. This is consistent with intuition and the life cycle theories, which suggest that product innovation is a highly fluid state, and innovative firms are competing based on who can innovate successfully and build the dominant design. As the market for the product is not yet established and innovation is the margin for competition, it is sensible that entrepreneurial firms would enter these markets.

One final note on outcomes is that IPOs and venture financing are also very likely to materialize in markets dominated by mature Life3 firms that also have higher Q. As Life3 firms are static and are not investing, this suggests that potential entrants are attracted to markets where incumbents are both profitable and are not behaving in an entrepreneurial manner. By not becoming more innovative, such incumbents leave the door relatively open for innovators to enter and potentially take market share later.

In all, the results of our panel data tests, both for investments and for outcomes, yield many new insights on the link between investments, outcomes and life cycles. Also noteworthy is that these results are within-firm results, and indicate that the same firm can behave differently in different situations. When firms move on the life cycle, or when their Q changes, they change their investments and their performance changes to resemble what theories of the life cycle would predict.

6 Impact of Major Shocks on the Life Cycle

We next examine whether major (plausibly exogenous) shocks can impact the patterns we documented earlier. For example, do firms become more mature and older following shocks like the financial crisis, or do they focus less on current sales and more on the future via innovation. We consider two shocks: the technology bust of 2000 to 2002 and the financial crisis of 2007 to 2009.

In particular, we restrict our sample to two years for each test. The first is the pre-shock year. For the technology bust, this is 1999. For the financial crisis, this is 2007. The second year is the post-treatment year. For the technology bust, this is 2001, and for the financial crisis, this is 2009. Our objective is to examine if the rate of transition through the life cycle is different in the treatment year than in the pre-crisis year. This is achieved by considering a post-treatment dummy, and interacting it with the life cycle progression variables shown in Table 6. In particular, we run the same panel data specification as in Table 6, except we restrict the sample to just these two years. All controls and fixed effects remain included. Our variables of interest are the life cycle interactions with the post-shock dummy.

[**Insert Table 14 Here**]

Table 14 displays the results. Panel A focuses on the technology bust from 1999 to 2001. Focusing on the Cross terms, for example Shock x Life1, we find that the technology bust increased transitions in the direction of young to old. Life1 firms transitioned to both Life2, Life3 and even delisting faster than in the control year. Life2 firms transitioned to Life3, Life4, and delisting faster than usual. These results indicate that this particular shock lead many firms to age quickly, in some cases moving two stages down the life cycle toward decline. These results in part help to validate the measure, as they are not particularly unexpected, but they also illustrate in formal terms the real consequences of shocks.

The table also shows that mature firms reacted differently to the shocks. Life3 firms shifted more toward process innovation and cost cutting, as more efficient production was likely necessary for long term profitability following the tech bust. Life4 firms weakly also moved toward cost cutting.

Panel B of Table 14 shows that the financial crisis of 2007 to 2009 resulted in materially the same outcomes for firms in the various life cycle stages. Life1 firms moved out of product innovation and into maturity (Life3) and decline (Life4). Life2 firms moved toward decline (Life4).

There is one surprising contrast between the technology bust in Panel A and the financial crisis in Panel B. Declining firms appear to have taken risky bets following the financial crisis and moved back up the life cycle toward more innovative stages. The most intense shift is toward process innovation and cost cutting, which is not particularly surprising given the need to preserve liquidity via lower costs during a financial crisis. However, more surprising is the shift also toward Life1 and Life3, indicating that the cost cutting was accompanied by some increase toward innovation. One interpretation is that declining firms were able to take advantage of the fact that the innovative firms seemed to age dramatically during this time. Given the void in innovation, it would seem more likely that a risky bet to save a declining firm from further decline might generate the best expected value for shareholders. Of course, this interpretation is speculative and we note that future research on this finding is likely to be fruitful.

The main finding in this section is further evidence that firms do not progress deterministically down the life cycle, and hence firm age is not likely to be an ideal proxy for life cycle progressions. Moreover, we conclude that negative shocks like the technology bust and the financial crisis tend to push innovative firms toward maturity and decline (premature aging). In some cases, however, older firms might find opportunistic ways to move back toward innovative stages.

6.1 Market Disruptions

We next examine if firms facing broad market disruption shocks experience changes in their life cycle status, investment, and outcomes. Market disruption is particularly relevant in a life cycle context, as by definition it would indicate that the standard strategies firms must adopt through the cycle are likely in need of revision. It is further relevant to understand if the changes in this environment are different for firms that are ex-ante in more innovative states, or in more mature states. We first identify for each firm the number of 10-K paragraphs that contain a word having the root "disrupt" and that also contain the word "market" or "markets". We then scale this count by the total number of paragraphs in the given 10-K. To reduce potential endogeneity concerns, we then focus only on very broad market disruption shocks that affect firms in many related product markets. The intuition is akin to how the market return is often used as an instrument, as it is unlikely that any one firm can endogenously influence the market overall. We thus measure the average market disruption of distant peers, those in the TNIC-2 industry database but are not in the TNIC-3 database (Hoberg and Phillips (2016)). These peers are akin to firms that are in the same two-digit SIC code but not the same three-digit SIC code, and hence they are broad peers. We also consider vertically related peers following Fresard, Hoberg and Phillips (2017). We regress various ex-post outcomes on ex-ante values of the life cycle variables and their interactions with the broad market disruption shocks.

Table 15 displays the results. The table shows that a primary effect of the shock is that many firms in various life cycle stages reinforce their current life cycle stage. This is the case for Life2, Life3, and Life4 as the shock increases loadings on these stages when firms ex-ante have higher loadings. However, in contrast, Life1 firms move more into the Life2 stage and thus focus on process. We also observe strong results on investment, as more mature firms in Life3 and Life4 increase CAPX following these shocks, whereas Life2 firms increase R&D and Life1 firms reduce both forms of investment. These results indicate that the shock indeed impacts the overall strategy each firm adopts.

The shocks also impact profits differently for each life cycle stage. Life1 firms experience rises in profitability whereas Life2 firms experience declines. Both are highly significant despite the firm fixed effects. Finally, we observe very strong decreases in competition as measured using total similarity for Life3 firms. This is likely because Life3 firms, being passive, are not the disruptors. The observed declining total similarity for these firms is instead consistent with their being disrupted, as other firms move away from their more obsolete products toward the newly emerging products. These results thus indicate a "silver lining" for disrupted mature firms: competition surrounding their existing products declines. This allows for the disrupted firms to offset the increased competition from the disruptors with increased product differentiation. Yet not surprisingly the overall impact is reduced profitability as the impact of the disruption exceeds the benefit of increased differentiation.

7 Conclusion

Motivated by theories of product life cycles, for example Abernathy and Utterback (1978), we develop a five-stage model of the product life cycle that aggregates to the firm-level based on firm product portfolios. The stages run from product innovation, to process innovation, to maturity and stability, and finally to decline and delisting. We build our life cycle model using text based analysis of firm 10-Ks. This approach allows us to re-categorize firms annually, and examine how firms progress through the life cycle, how they invest, and ultimate outcomes.

We find that a host of firm investment and acquisition decisions are strongly related to the firm's position in the life cycle, and also to interactions with the firm's Tobins' Q. Younger firms doing product innovation focus on R&D, firms focused on process innovation invest in CAPX, and firms that are in more mature stages invest in acquisitions. This latter result is consistent with these firms investing in external growth given that internal growth options are exhausted. Firms in decline specialize in selling assets, particularly to more innovative firms in younger stages of the life cycle. However, these patterns shift when a firm's Q rises. For example, declining firms become more aggressive and shift from sellers of assets to buyers.

Overall, although firms tend to move through the life cycle in the direction predicted by theory, we find that firm age cannot explain the very rich results we find when we examine the aging process through the lens of life cycle stages. Many corporate finance activities appear in later or middle stages, and other activities appear early and then disappear. Hence the relationship between many corporate finance policies are highly non-linear in their relationship with age. Moreover, because firms at times move backwards in the life cycle, there is considerable variation in the relationship between policies and the progression of firms through the cycle that particularly cannot be seen by studying age alone.

We believe that examining many corporate finance policies through the lens of the product life cycle can yield many novel results in finance and economics. In many cases, the economic size of gains in explanatory power are very large. For example, we see large gains in the explanatory power of basic investment-Tobins' Q regressions when the level of Q is conditioned on the state of the life cycle. Moreover, the explanatory power of this conditional model increases throughout our sample whereas the explanatory power of a basic model drops over time. This suggests that information about a firm's life cycle is becoming increasingly important in understanding firms in the "new economy".

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Table 1: Summary Statistics

Summary statistics are reported for our sample of 77,839 observations based on annual firm observations from 1997 to 2015. The variables Life1-Life4 are based on textual queries to firm 10-Ks in each year. Life1 measures the intensity of product innovation, Life2 measures the intensity of process innovation, Life3 measures the intensity of stable and mature products, and Life4 measures the intensity of product decline (discontinuation). All variables are described in detail in Section 3.

Variable	Mean	Std. Dev.	Minimum	Median	Maximum	# Obs
Panel A: Life Cycle Variables						
Life1	0.255	0.133	0.000	0.241	0.954	77,547
Life2	0.395	0.158	0.016	0.370	0.992	77,547
Life3	0.302	0.131	0.004	0.294	0.965	77,547
Life4	0.048	0.064	0.000	0.027	0.891	77,547
LifeDelist	0.016	0.125	0.000	0.000	1.000	77,547
Panel B: Investment, M&A, and Tobins' Q						
R&D/Assets	0.046	0.105	0.000	0.000	0.841	77,547
CAPX/Assets	0.045	0.059	-0.000	0.026	0.505	77,547
Acquisition Dummy	0.342	0.474	0.000	0.000	1.000	77,547
Target Dummy	0.185	0.389	0.000	0.000	1.000	77,547
Full Acquirer Dummy	0.121	0.326	0.000	0.000	1.000	77,547
Full Target Dummy	0.047	0.212	0.000	0.000	1.000	77,547
Tobins Q	1.547	1.812	0.080	1.035	34.202	77,547
Panel C: Outcome Variables						
OI/Sales	0.085	0.328	-1.000	0.122	0.851	77,547
OI/Assets	0.049	0.201	-1.000	0.082	0.781	77,547
Sales Growth	0.098	0.425	-6.177	0.070	9.383	77,547
TNIC-3 IPO Rate	0.028	0.056	0.000	0.004	1.000	77,547
SIC-3 IPO Rate	0.017	0.027	0.000	0.005	1.000	77,547
IPO Text Similarity	9.675	3.789	1.157	9.373	26.007	70,295
VC Text Similarity	13.889	5.607	2.493	13.312	30.653	70,295
Panel D: Additional Controls						
Log Firm Age	2.643	0.762	0.693	2.639	4.190	77,547
Log Assets	6.057	2.090	1.330	6.051	11.580	77,547
Log 10K Size	6.072	0.548	4.585	6.087	7.607	77,547

Table 2: Pearson Correlation Coefficients

Pearson Correlation Coefficients are reported for our sample of 77,839 observations based on annual firm observations from 1997 to 2015. The variables Life1-Life4 are based on textual queries to firm 10-Ks in each year. Life1 measures the intensity of product innovation, Life2 measures the intensity of process innovation, Life3 measures the intensity of stable and mature products, and Life4 measures the intensity of product decline (discontinuation). All variables are described in detail in Section 3.

Row Variable	Life1	Life2	Life3	Life4	Life Delist	Log Age	Log Assets	Tobins Q	OI/ Sales	Sales Growth	R&D/ Assets	CAPX/ Assets	Acquirer Dummy
					Correlation Coefficients								
Life2	-0.603												
Life3	-0.215	-0.554											
Life4	-0.145	-0.086	-0.234										
Life Delist	-0.015	0.001	-0.011	0.051									
Log Firm Age	-0.183	0.164	-0.097	0.174	-0.038								
Log Assets	-0.246	0.113	0.119	-0.013	-0.136	0.321							
Tobins Q	0.279	-0.090	-0.151	-0.046	-0.021	-0.086	-0.228						
OI/Sales	-0.343	0.166	0.183	-0.074	-0.109	0.146	0.421	-0.177					
Sales Growth	0.089	-0.025	0.009	-0.142	-0.068	-0.149	-0.004	0.160	0.034				
R&D/Assets	0.515	-0.272	-0.193	-0.002	0.056	-0.133	-0.335	0.329	-0.545	0.025			
CAPX/Assets	-0.131	0.329	-0.241	-0.049	-0.014	-0.010	-0.038	0.092	-0.004	0.089	-0.039		
Acquirer Dummy	-0.036	-0.013	0.060	-0.015	-0.066	0.093	0.294	0.007	0.125	0.086	-0.098	0.005	
Target Dummy	-0.101	0.033	-0.023	0.178	0.016	0.177	0.254	-0.056	0.043	-0.062	-0.061	0.014	0.174

Table 3: Market Power and Globalization Metrics vs Firm Size and Dynamism

The table reports average values of four market power and globalization metrics for two-way tercile sorts. The four variables are noted in the panel headers and include Total Similarity, OI/assets, Offshore Output Text, and Offshore Input Text. We form terciles using independent sorts of log assets and the firm dynamism index (which is computed as $log[\frac{Life1+Life2+Life4}{Life3}]$). Terciles are formed separately in each year. We then report the average value of each aforementioned variable in each of the 9 subsamples.

Firm Size Tercile	Dynamic Firm Tercile 1	Dynamic Firm Tercile 2	Dynamic Firm Tercile 3
	Panel A: Average Total Similarity		
Small Firms	3.6	3.2	6.8
Medium Firms	20.0	8.8	7.1
Large Firms	19.7	9.2	6.6
	Panel B: Average Profitability (OI/assets)		
Small Firms	0.027	-0.011	-0.084
Medium Firms	0.077	0.095	0.083
Large Firms	0.079	0.109	0.115
	Panel C: Average Offshore Output Text		
Small Firms	0.054	0.069	0.060
Medium Firms	0.037	0.065	0.061
Large Firms	0.036	0.058	0.061
	Panel D: Average Offshore Input Text		
Small Firms	0.032	0.042	0.039
Medium Firms	0.024	0.050	0.054
Large Firms	0.027	0.056	0.065

Table 4: Product Life Cycle and Firm Age

The table reports OLS estimates for our sample of annual firm observations from 1997 to 2015. An observation is one firm in one year. The dependent variable is a life cycle variable and is indicated in the first row. All rows include firm and year fixed effects, and standard errors are clustered by firm. Panel A reports results for a pure life cycle versus firm age model, and Panel B adds key control variables. t-statistics are in parentheses.

Row	Dependent Variable	Log Age	Log Assets	Tobins Q	10-K Size	Obs./ Adj R^2
		Panel A: Firm and Year Fixed Effects				
(1)	Life1	-0.036				79,032
		(-2.24)				0.808
(2)	Life2	-0.079				79,032
		(-5.35)				0.820
(3)	Life3	0.081				79,032
		(4.38)				0.723
(4)	Life4	0.104				79,032
		(4.82)				0.502
(5)	LifeDelist	0.016				79,032
		(11.3)				0.379
		Panel B: Firm and Year Fixed Effects Plus Controls				
(6)	Life1	-0.068	0.085	0.046	-0.117	76,798
		(-3.89)	(5.82)	(13.0)	(-24.6)	0.818
(7)	Life2	-0.089	-0.027	-0.024	-0.013	76,798
		(-5.24)	(-1.85)	(-8.11)	(-3.07)	0.823
(8)	Life3	0.104	-0.003	0.002	0.150	76,798
		(5.07)	(-0.18)	(0.56)	(19.8)	0.736
(9)	Life4	0.148	-0.106	-0.041	-0.032	76,798
		(5.90)	(-4.49)	(-8.85)	(-6.29)	0.509
(10)	LifeDelist	0.025	-0.034	-0.005	0.002	76,798
		(14.3)	(-13.5)	(-7.41)	(2.77)	0.388

Table 5: Product Market Fluidity and Product Description Growth

The table reports OLS estimates for our sample of annual firm observations from 1997 to 2015. An observation is one firm in one year. The dependent variable is product market fluidity (see Hoberg, Phillips and Prabhala (2014)) or product description growth (see Hoberg and Phillips (2010)) in Panel A and Panel B, respectively. All specifications include firm and year fixed effects. Standard errors are clustered by firm. t-statistics are in parentheses.

Row	Life1	Life2	Life3	Life4	TobQ x Life1	TobQ x Life2	TobQ x Life3	TobQ x Life4	Log Age	Log Assets	Business Descr. Size	Whole 10-K Size	Tobins Q	Obs/ Adj R^2
							Panel A: Dependent Variable = Product Description Growth							
(1)	0.042	-0.015	0.000	-0.036							-1.519	0.023		70,793
	(4.02)	(-1.43)		(-6.45)							(-67.4)	(3.65)		0.306
(2)	0.033	-0.018	0.000	-0.031					-0.187	0.178	-1.559	0.019	0.065	70,405
	(3.11)	(-1.64)		(-5.88)					(-7.31)	(7.57)	(-66.8)	(2.94)	(10.0)	0.311
(3)	0.032	-0.012	0.000	-0.027	0.036	-0.003	0.024	-0.005	-0.194	0.166	-1.556	0.019		70,781
	(2.89)	(-1.07)		(-4.55)	(3.52)	(-0.30)	(2.51)	(-0.79)	(-7.60)	(7.07)	(-66.8)	(3.01)		0.310
							Panel B: Dependent Variable = Product Market Fluidity							
(4)	0.034	-0.007	0.000	-0.001							0.628	0.014		71,436
	(6.10)	(-1.22)		(-0.44)							(51.8)	(4.47)		0.841
(5)	0.030	-0.008	0.000	0.001					-0.088	0.101	0.607	0.011	0.028	71,045
	(5.28)	(-1.38)		(0.57)					(-5.80)	(7.95)	(49.3)	(3.67)	(9.02)	0.842
(6)	0.029	-0.005	0.000	0.004	0.018	-0.005	0.008	-0.003	-0.091	0.095	0.609	0.011		71,424
	(4.77)	(-0.89)		(1.33)	(3.49)	(-1.08)	(1.90)	(-1.26)	(-6.02)	(7.48)	(49.4)	(3.69)		0.841

Table 6: Life Cycle Transitions

The table reports OLS estimates for our sample of annual firm observations from 1997 to 2015. One observation is one firm in one year. The dependent variable is an ex-post firm-specific life cycle variable in year $t+1$ as noted in the first column. All RHS variables are measured in year t and are ex-ante observable. We include the ex-ante life cycle variables as RHS variables, and we excluding Life3 as the four variables (Life1 to Life4) sum to unity and are collinear with the intercept. Hence the coefficients for the remaining three variables should be interpreted as transition intensities relative to Life3 firms as the benchmark. We also include cross terms with Tobins Q to examine if life cycles transition differently when firms have high valuations. All specifications include year fixed effects. Standard errors are clustered by firm. t-statistics are in parentheses.

Dependent RowVariable	Life1	Life2	Life3	Life4	TobQ x Life1	TobQ x Life2	TobQ x Life3	TobQ x Life4	Tobins Q	Log Age	Log Assets	Whole 10-K Size	Obs/ Adj R^2
						Panel A: Baseline Life Cycle Results							
(1) Life1	0.828	-0.036	0.000	-0.026						-0.001	-0.004	0.000	78,526
	(254.3)	(-17.7)		(-6.59)						(-2.06)	(-25.0)	(26.9)	0.783
(5) Life2	-0.041	0.855	0.000	0.067						0.002	0.001	-0.000	78,526
	(-14.3)	(262.7)		(7.70)						(4.46)	(4.41)	(-7.38)	0.785
(9) Life3	0.042	0.000	0.798	0.229						-0.008	0.005	-0.000	78,526
	(15.1)		(119.6)	(4.85)						(-8.44)	(18.2)	(-23.8)	0.645
(13)Life4	-0.030	-0.021	0.000	0.528						0.007	-0.002	0.000	78,526
	(-4.13)	(-3.31)		(8.92)						(6.95)	(-8.23)	(17.9)	0.421
(17)LifeDelist	-0.025	0.002	0.000	0.055						0.001	-0.008	0.000	78,526
	(-5.67)	(0.61)		(5.39)						(1.78)	(-24.2)	(10.9)	0.019
						Panel B: Add Tobins Q Cross Terms							
(2) Life1	0.813	-0.039	0.000	-0.039	0.004	0.001	-0.001	0.009		-0.001	-0.003	0.000	77,170
	(187.3)	(-14.6)		(-6.04)	(4.50)	(1.27)	(-0.63)	(2.26)		(-1.69)	(-22.6)	(25.8)	0.785
(6) Life2	-0.032	0.853	0.000	0.078	-0.003	0.003	0.001	-0.007		0.002	0.001	-0.000	77,170
	(-8.20)	(225.0)		(7.71)	(-4.13)	(4.65)	(1.57)	(-2.28)		(4.97)	(5.21)	(-7.35)	0.787
(10)Life3	0.046	0.000	0.798	0.210	-0.002	-0.001	-0.001	0.014		-0.009	0.004	-0.000	77,170
	(12.5)		(122.4)	(5.59)	(-2.24)	(-2.90)	(-0.79)	(1.11)		(-8.70)	(16.9)	(-22.9)	0.646
(14)Life4	-0.030	-0.016	0.000	0.549	0.001	-0.002	0.001	-0.016		0.007	-0.002	0.000	77,170
	(-3.94)	(-2.79)		(11.1)	(1.86)	(-8.45)	(0.62)	(-1.29)		(6.81)	(-8.76)	(17.6)	0.423
(18)LifeDelist	-0.016	0.013	0.000	0.063	-0.001	-0.005	-0.001	-0.008		0.001	-0.008	0.000	77,170
	(-2.73)	(2.91)		(5.40)	(-0.63)	(-8.02)	(-1.11)	(-1.66)		(0.82)	(-25.0)	(11.5)	0.022

Table 7: Life Cycle Transitions (Manufacturing Only)

The table reports OLS estimates for our sample of annual firm observations from 1997 to 2015, however we restrict the sample to manufacturing firms only. Manufacturing firms are those having SIC codes in the interval (2000,3999). One observation is one firm in one year. The dependent variable is an ex-post firm-specific life cycle variable in year $t+1$ as noted in the first column. All RHS variables are measured in year t and are ex-ante observable. We include the ex-ante life cycle variables as RHS variables, and we excluding Life3 as the four variables (Life1 to Life4) sum to unity and are collinear with the intercept. Hence the coefficients for the remaining three variables should be interpreted as transition intensities relative to Life3 firms as the benchmark. We also include cross terms with Tobins Q to examine if life cycles transition differently when firms have high valuations. All specifications include year fixed effects. Standard errors are clustered by firm. t-statistics are in parentheses.

Dependent RowVariable	Life1	Life2	Life3	Life4	TobQ x Life1	TobQ x Life2	TobQ x Life3	TobQ x Life4	Tobins Q	Log Age	Log Assets	Whole 10-K Size	Obs/ Adj R^2
					Panel A: Baseline Life Cycle Results								
(3) Life1	0.856	-0.018	0.000	-0.023						-0.002	-0.004	0.000	30,223
	(162.6)	(-4.01)		(-2.42)						(-3.92)	(-17.5)	(23.9)	0.822
(7) Life2	-0.083	0.771	0.000	0.020						0.000	0.003	-0.000	30,223
	(-15.2)	(107.7)		(1.30)						(0.12)	(12.6)	(-9.04)	0.745
(11)Life3	-0.008	0.000	0.714	0.152						-0.002	0.002	-0.000	30,223
	(-1.91)		(69.3)	(4.49)						(-2.56)	(6.04)	(-17.5)	0.560
(15)Life4	-0.051	-0.039	0.000	0.565						0.004	-0.001	0.000	30,223
	(-5.92)	(-4.33)		(11.9)						(6.52)	(-5.77)	(9.16)	0.454
(19)LifeDelist	-0.038	0.015	0.000	0.048						-0.000	-0.008	0.000	30,223
	(-5.09)	(1.76)		(3.45)						(-0.14)	(-15.3)	(6.06)	0.019
					Panel B: Add Tobins Q Cross Terms								
(4) Life1	0.855	-0.031	0.000	-0.027	-0.003	0.011	0.001	0.006		-0.002	-0.004	0.000	29,841
	(101.8)	(-4.87)		(-2.12)	(-1.83)	(6.77)	(0.47)	(1.20)		(-3.07)	(-17.1)	(23.8)	0.825
(8) Life2	-0.089	0.788	0.000	0.016	0.006	-0.012	-0.001	0.002		0.000	0.003	-0.000	29,841
	(-11.1)	(83.9)		(0.73)	(5.38)	(-7.21)	(-0.45)	(0.26)		(0.06)	(12.2)	(-9.08)	0.747
(12)Life3	0.007	0.000	0.716	0.173	-0.004	0.004	0.003	-0.011		-0.002	0.002	-0.000	29,841
	(1.18)		(52.3)	(3.32)	(-3.52)	(2.44)	(1.03)	(-0.78)		(-2.56)	(5.93)	(-17.4)	0.562
(16)Life4	-0.056	-0.042	0.000	0.555	0.001	-0.003	-0.003	0.003		0.003	-0.001	0.000	29,841
	(-4.18)	(-3.33)		(7.75)	(2.06)	(-2.99)	(-1.21)	(0.20)		(6.10)	(-5.88)	(9.33)	0.456
(20)LifeDelist	-0.029	0.025	0.000	0.056	0.000	-0.007	0.000	-0.006		-0.001	-0.008	0.000	29,841
	(-2.68)	(2.12)		(2.68)	(0.13)	(-3.03)	(0.17)	(-0.71)		(-1.06)	(-15.2)	(6.22)	0.020

Table 8: CAPX Investment-Q Regressions

The table reports selected results from annual OLS investment-Q regressions from 1997 to 2015. Regressions are run separately in each year and each regression is purely cross sectional, as one observation is one firm. The dependent variable in all models is ex post CAPX/assets in year $t+1$. All RHS variables are ex ante and are observable in year t. In all, the results below are based on four models. The first block of four columns is a basic investment-Q regression where CAPX is regressed on ex-ante Tobins Q plus basic controls. The second block of 9 columns is the conditional model, where Tobins Q is regressed on the life variables and their cross terms with Tobins Q (here controls for log age and log assets are included but are not reported to conserve space). The last two columns indicate the adjusted R^2 results when the basic and conditional model are run at the industry level instead of at the firm level. In particular, industry level regressions are conducted by averaging both the dependent variable and the RHS variables within each SIC-3 industry in each year, and then running the annual cross sectional investment-Q regressions using the resulting industry-year panel. t-statistics are in parentheses.

		Basic Model				Conditional Model									Industry Models	
															(Basic)	(Condit.)
Row	Year	Tobins Q	Log Age	Log Assets	Adj. R^2	Life1	Life2	Life3	Life4	TobQ x Life1	TobQ x Life2	TobQ x Life3	TobQ x Life4	Adj R^2	Adj R^2	Adj R^2
(1)	1998	0.475	-0.000	-0.000	0.011	0.090	0.173	N/A	0.074	-0.712	0.799	2.376	-3.019	0.105	-0.004	0.141
		(7.93)	(-0.28)	(-0.13)		(7.37)	(17.0)		(3.05)	(-2.94)	(3.49)	(7.59)	(-2.52)			
(2)	1999	0.204	0.004	-0.001	0.008	0.068	0.137	N/A	0.002	-0.357	-0.304	1.590	-0.150	0.081	-0.010	0.120
		(5.40)	(3.91)	(-2.60)		(7.64)	(18.5)		(0.11)	(-2.30)	(-2.18)	(9.01)	(-0.15)			
(3)	2000	0.138	0.005	-0.002	0.017	0.063	0.120	N/A	-0.022	-0.513	-0.081	1.236	0.438	0.080	0.009	0.134
		(7.42)	(4.49)	(-5.39)		(6.99)	(16.6)		(-1.27)	(-5.33)	(-1.04)	(11.0)	(1.06)			
(4)	2001	0.331	0.005	-0.001	0.024	0.060	0.124	N/A	0.036	-0.383	0.422	1.525	-0.883	0.099	0.025	0.121
		(10.7)	(4.54)	(-2.38)		(6.77)	(16.7)		(2.13)	(-3.08)	(3.29)	(8.76)	(-1.25)			
(5)	2002	0.364	0.007	-0.001	0.029	0.057	0.118	N/A	-0.006	-0.293	0.028	1.392	2.571	0.113	0.053	0.181
		(9.90)	(6.90)	(-2.90)		(7.17)	(18.0)		(-0.44)	(-1.95)	(0.22)	(7.13)	(3.32)			
(6)	2003	0.512	0.006	-0.001	0.033	0.046	0.130	N/A	-0.003	-0.014	0.064	1.472	2.475	0.148	0.152	0.273
		(10.6)	(6.61)	(-1.94)		(5.61)	(19.6)		(-0.18)	(-0.07)	(0.44)	(6.21)	(2.87)			
(7)	2004	0.255	0.006	-0.001	0.019	0.048	0.148	N/A	0.002	-0.216	-0.256	1.335	2.213	0.146	0.020	0.142
		(6.57)	(5.91)	(-3.18)		(5.30)	(21.0)		(0.14)	(-1.28)	(-2.41)	(6.87)	(2.92)			
(8)	2005	0.344	0.006	-0.001	0.020	0.060	0.174	N/A	0.015	-0.240	-0.082	1.584	0.830	0.162	0.011	0.180
		(6.84)	(5.08)	(-2.47)		(5.33)	(20.1)		(0.85)	(-1.08)	(-0.58)	(6.41)	(0.92)			
(9)	2006	0.543	0.005	0.000	0.020	0.056	0.193	N/A	0.013	-0.581	0.498	1.917	1.860	0.198	0.015	0.213
		(8.37)	(3.73)	(0.10)		(4.24)	(19.0)		(0.60)	(-2.08)	(2.51)	(6.18)	(1.55)			
(10)	2007	0.373	0.001	0.001	0.010	0.043	0.228	N/A	0.028	0.313	-0.498	1.658	1.845	0.206	-0.001	0.155
		(6.46)	(0.49)	(2.02)		(3.35)	(24.1)		(1.30)	(1.32)	(-3.47)	(6.25)	(1.59)			
(11)	2008	0.563	-0.003	0.002	0.018	0.065	0.251	N/A	-0.001	-0.360	0.002	1.946	3.721	0.233	0.043	0.161
		(8.51)	(-1.86)	(2.79)		(4.60)	(24.1)		(-0.04)	(-1.26)	(0.01)	(6.07)	(2.82)			
(12)	2009	0.616	-0.000	0.001	0.019	0.039	0.158	N/A	0.002	-0.327	-0.073	2.238	3.870	0.198	0.083	0.253
		(9.00)	(-0.28)	(2.42)		(3.95)	(21.7)		(0.09)	(-1.18)	(-0.39)	(6.85)	(2.80)			
(13)	2010	0.480	-0.001	0.001	0.016	0.054	0.161	N/A	0.024	-0.735	0.181	2.197	0.927	0.193	0.082	0.190
		(7.94)	(-0.99)	(2.42)		(5.21)	(21.1)		(1.32)	(-3.06)	(1.11)	(7.98)	(0.80)			
(14)	2011	0.432	-0.001	0.001	0.013	0.057	0.201	N/A	0.028	-0.428	-0.247	2.085	1.489	0.216	0.036	0.185
		(7.11)	(-0.42)	(2.42)		(4.89)	(23.4)		(1.26)	(-1.82)	(-1.59)	(7.97)	(1.15)			
(15)	2012	0.516	-0.003	0.001	0.015	0.058	0.227	N/A	0.010	-0.732	-0.375	2.652	3.645	0.249	0.021	0.239
		(6.93)	(-1.89)	(2.24)		(4.52)	(24.1)		(0.37)	(-2.47)	(-2.02)	(7.97)	(2.05)			
(16)	2013	0.385	-0.001	0.001	0.012	0.037	0.203	N/A	0.068	-0.101	-0.372	2.197	-0.516	0.234	0.022	0.226
		(6.27)	(-0.72)	(1.92)		(3.04)	(23.6)		(3.37)	(-0.41)	(-2.42)	(7.83)	(-0.53)			
(17)	2014	0.363	-0.003	0.002	0.011	0.033	0.223	N/A	0.051	-0.123	-0.283	2.160	1.185	0.227	0.000	0.158
		(5.54)	(-1.70)	(2.89)		(2.34)	(21.2)		(2.01)	(-0.48)	(-1.39)	(6.92)	(0.94)			
(18)	2015	0.212	-0.003	0.002	0.006	0.030	0.216	N/A	0.041	-0.045	-0.611	1.966	2.249	0.222	-0.004	0.121
		(3.38)	(-2.10)	(3.56)		(2.26)	(21.4)		(1.55)	(-0.19)	(-2.99)	(6.58)	(1.45)			

Table 9: R&D Investment-Q Regressions

The table reports selected results from annual OLS investment-Q regressions from 1997 to 2015. Regressions are run separately in each year and each regression is purely cross sectional, as one observation is one firm. The dependent variable in all models is ex post R&D/assets in year $t+1$. All RHS variables are ex ante and are observable in year t. In all, the results below are based on four models. The first block of four columns is a basic investment-Q regression where R&D is regressed on ex-ante Tobins Q plus basic controls. The second block of 9 columns is the conditional model, where Tobins Q is regressed on the life variables and their cross terms with Tobins Q (here controls for log age and log assets are included but are not reported to conserve space). The last two columns indicate the adjusted R^2 results when the basic and conditional model are run at the industry level instead of at the firm level. In particular, industry level regressions are conducted by averaging both the dependent variable and the RHS variables within each SIC-3 industry in each year, and then running the annual cross sectional investment-Q regressions using the resulting industry-year panel. t-statistics are in parentheses.

	Basic Model				Conditional Model									Industry Models	
														(Basic)	(Condit.)
Row Year	Tobins Q	Log Age	Log Assets	Adj. R^2	Life1	Life2	Life3	Life4	TobQ x Life1	TobQ x Life2	TobQ x Life3	TobQ x Life4	Adj R^2	Adj R^2	Adj R^2
(1) 1998	1.998	-0.004	-0.012	0.156	0.171	-0.021	N/A	0.004	6.304	-0.222	-3.884	5.101	0.341	0.133	0.421
	(23.3)	(-1.95)	(-15.1)		(10.6)	(-1.58)		(0.12)	(19.6)	(-0.73)	(-9.34)	(3.21)			
(2) 1999	1.232	-0.002	-0.014	0.143	0.259	-0.001	N/A	0.055	3.391	-0.127	-1.913	3.398	0.333	0.132	0.352
	(18.8)	(-1.17)	(-18.5)		(18.4)	(-0.12)		(1.73)	(13.7)	(-0.57)	(-6.83)	(2.19)			
(3) 2000	0.444	0.001	-0.014	0.147	0.239	-0.009	N/A	0.081	0.891	0.083	-0.485	0.506	0.287	0.307	0.451
	(16.8)	(0.48)	(-21.6)		(19.9)	(-0.94)		(3.54)	(6.92)	(0.80)	(-3.22)	(0.92)			
(4) 2001	1.213	-0.012	-0.014	0.174	0.274	-0.003	N/A	0.071	1.950	0.068	-0.619	2.512	0.316	0.288	0.513
	(22.2)	(-6.10)	(-18.1)		(18.4)	(-0.23)		(2.47)	(9.32)	(0.31)	(-2.11)	(2.11)			
(5) 2002	1.845	-0.013	-0.013	0.172	0.245	-0.014	N/A	0.033	5.014	0.099	-3.547	4.511	0.359	0.124	0.401
	(21.3)	(-5.80)	(-16.2)		(14.2)	(-1.01)		(1.04)	(15.4)	(0.36)	(-8.37)	(2.68)			
(6) 2003	1.223	-0.010	-0.012	0.139	0.247	-0.002	N/A	0.028	4.090	-0.114	-2.709	3.308	0.359	0.089	0.398
	(13.1)	(-5.33)	(-17.7)		(17.0)	(-0.19)		(1.12)	(11.1)	(-0.44)	(-6.42)	(2.16)			
(7) 2004	0.975	-0.005	-0.009	0.133	0.253	0.013	N/A	0.047	3.334	-0.006	-2.319	2.036	0.359	0.083	0.322
	(14.5)	(-2.83)	(-14.1)		(17.6)	(1.20)		(1.99)	(12.4)	(-0.04)	(-7.49)	(1.68)			
(8) 2005	1.403	-0.007	-0.011	0.168	0.230	0.027	N/A	0.079	5.783	-0.607	-2.445	-2.201	0.425	0.092	0.402
	(17.1)	(-3.30)	(-14.0)		(13.8)	(2.10)		(2.98)	(17.8)	(-2.92)	(-6.72)	(-1.65)			
(9) 2006	1.541	-0.006	-0.012	0.162	0.267	0.041	N/A	0.116	5.737	-0.744	-2.551	-3.399	0.422	0.082	0.337
	(15.8)	(-2.88)	(-15.0)		(14.6)	(2.91)		(3.84)	(14.8)	(-2.72)	(-5.95)	(-2.05)			
(10) 2007	1.319	-0.006	-0.014	0.144	0.313	0.057	N/A	0.131	6.167	-0.778	-2.937	-3.602	0.426	0.091	0.363
	(13.8)	(-2.43)	(-15.0)		(16.2)	(3.96)		(4.09)	(17.2)	(-3.58)	(-7.31)	(-2.05)			
(11) 2008	1.479	-0.003	-0.016	0.140	0.331	0.047	N/A	0.109	7.458	-0.792	-4.215	-1.239	0.420	0.085	0.474
	(13.6)	(-1.08)	(-15.7)		(15.3)	(2.93)		(3.01)	(17.2)	(-3.13)	(-8.61)	(-0.61)			
(12) 2009	2.003	-0.002	-0.015	0.148	0.273	0.036	N/A	0.039	8.437	-0.947	-4.015	3.970	0.385	0.091	0.507
	(13.8)	(-0.85)	(-17.2)		(14.0)	(2.47)		(1.11)	(15.2)	(-2.55)	(-6.17)	(1.44)			
(13) 2010	1.819	0.002	-0.012	0.192	0.211	0.025	N/A	0.010	6.747	-0.724	-3.150	5.656	0.440	0.135	0.509
	(18.3)	(0.86)	(-16.3)		(13.4)	(2.19)		(0.37)	(18.5)	(-2.93)	(-7.56)	(3.21)			
(14) 2011	1.617	-0.002	-0.011	0.180	0.262	0.046	N/A	0.014	4.914	-0.443	-2.262	7.930	0.423	0.149	0.407
	(17.3)	(-0.98)	(-14.6)		(15.5)	(3.68)		(0.44)	(14.4)	(-1.97)	(-5.98)	(4.23)			
(15) 2012	1.335	-0.003	-0.013	0.151	0.286	0.041	N/A	0.023	4.108	-0.477	-1.743	7.781	0.376	0.128	0.442
	(12.4)	(-1.31)	(-15.4)		(15.6)	(3.03)		(0.63)	(9.74)	(-1.81)	(-3.69)	(3.08)			
(16) 2013	1.336	-0.002	-0.014	0.161	0.280	0.034	N/A	0.129	5.311	-0.497	-2.317	-2.224	0.383	0.120	0.451
	(12.9)	(-0.79)	(-15.3)		(14.1)	(2.36)		(3.85)	(12.9)	(-1.96)	(-5.00)	(-1.38)			
(17) 2014	1.662	-0.004	-0.012	0.197	0.251	0.049	N/A	0.098	5.114	-1.118	-1.334	-0.664	0.410	0.151	0.485
	(17.1)	(-1.47)	(-14.1)		(12.3)	(3.25)		(2.71)	(13.8)	(-3.83)	(-2.98)	(-0.37)			
(18) 2015	1.839	-0.007	-0.014	0.224	0.295	0.050	N/A	0.031	4.197	-0.743	-1.233	4.855	0.426	0.132	0.452
	(17.6)	(-2.77)	(-15.6)		(13.9)	(3.08)		(0.72)	(11.3)	(-2.24)	(-2.55)	(1.93)			

Table 10: Acquisition Dummy Investment-Q Regressions

The table reports selected results from annual OLS investment-Q regressions from 1997 to 2015. Regressions are run separately in each year and each regression is purely cross sectional, as one observation is one firm. The dependent variable in all models is ex post acquirer dummy in year $t+1$. All RHS variables are ex ante and are observable in year t. In all, the results below are based on four models. The first block of four columns is a basic investment-Q regression where the acquisition dummy is regressed on ex-ante Tobins Q plus basic controls. The second block of 9 columns is the conditional model, where Tobins Q is regressed on the life variables and their cross terms with Tobins Q (here controls for log age and log assets are included but are not reported to conserve space). The last two columns indicate the adjusted R^2 results when the basic and conditional model are run at the industry level instead of at the firm level. In particular, industry level regressions are conducted by averaging both the dependent variable and the RHS variables within each SIC-3 industry in each year, and then running the annual cross sectional investment-Q regressions using the resulting industry-year panel. t-statistics are in parentheses.

	Basic Model				Conditional Model									Industry Models	
														(Basic)	(Condit.)
Row Year	Tobins Q	Log Age	Log Assets	Adj. R^2	Life1	Life2	Life3	Life4	TobQ x Life1	TobQ x Life2	TobQ x Life3	TobQ x Life4	Adj R^2	Adj R^2	Adj R^2
(1) 1998	2.628	-0.019	0.075	0.083	0.261	0.082	N/A	0.338	-7.107	1.538	18.08	-7.811	0.095	0.103	0.142
	(7.22)	(-2.30)	(22.7)		(3.36)	(1.27)		(2.18)	(-4.63)	(1.06)	(9.09)	(-1.03)			
(2) 1999	2.713	0.007	0.070	0.087	0.118	-0.000	N/A	-0.117	-0.736	-0.083	8.753	9.603	0.091	0.059	0.135
	(9.37)	(0.81)	(21.7)		(1.67)	(-0.01)		(-0.73)	(-0.60)	(-0.07)	(6.25)	(1.24)			
(3) 2000	1.745	0.012	0.068	0.095	0.256	-0.065	N/A	-0.167	-1.693	2.285	4.959	2.939	0.103	0.189	0.204
	(13.5)	(1.46)	(21.3)		(4.00)	(-1.25)		(-1.37)	(-2.46)	(4.09)	(6.16)	(1.00)			
(4) 2001	1.861	0.006	0.070	0.096	0.250	-0.085	N/A	-0.112	-3.541	2.954	7.993	-2.999	0.107	0.117	0.250
	(8.41)	(0.79)	(22.8)		(3.78)	(-1.54)		(-0.88)	(-3.83)	(3.10)	(6.18)	(-0.57)			
(5) 2002	2.473	0.015	0.067	0.091	0.317	0.045	N/A	0.008	-7.293	0.392	16.58	10.56	0.105	0.068	0.098
	(7.50)	(1.78)	(21.1)		(4.31)	(0.75)		(0.06)	(-5.23)	(0.33)	(9.13)	(1.47)			
(6) 2003	3.156	-0.004	0.067	0.085	0.240	0.005	N/A	-0.052	-6.184	0.746	14.17	21.41	0.092	0.087	0.106
	(6.75)	(-0.43)	(20.3)		(2.85)	(0.07)		(-0.36)	(-2.91)	(0.50)	(5.81)	(2.42)			
(7) 2004	1.721	0.003	0.057	0.055	0.323	0.055	N/A	0.094	-5.520	0.280	12.22	-5.618	0.064	0.026	0.039
	(4.68)	(0.29)	(15.6)		(3.53)	(0.78)		(0.63)	(-3.24)	(0.26)	(6.21)	(-0.73)			
(8) 2005	2.801	0.022	0.069	0.073	0.114	-0.046	N/A	0.006	-3.023	1.415	11.95	1.217	0.079	0.064	0.106
	(6.38)	(2.03)	(16.9)		(1.06)	(-0.57)		(0.03)	(-1.45)	(1.06)	(5.13)	(0.14)			
(9) 2006	3.397	0.008	0.076	0.083	0.121	0.097	N/A	0.114	-3.924	-0.658	18.24	13.98	0.092	0.047	0.097
	(6.52)	(0.71)	(18.3)		(1.03)	(1.09)		(0.59)	(-1.59)	(-0.38)	(6.65)	(1.32)			
(10) 2007	1.645	-0.010	0.072	0.075	0.072	-0.048	N/A	0.185	-4.175	-0.635	12.78	11.42	0.085	0.028	0.049
	(3.82)	(-0.94)	(17.6)		(0.68)	(-0.61)		(1.05)	(-2.12)	(-0.53)	(5.81)	(1.19)			
(11) 2008	2.795	0.029	0.069	0.080	0.187	0.040	N/A	0.052	-2.802	-0.880	15.69	3.213	0.089	0.072	0.153
	(6.42)	(2.89)	(17.1)		(1.79)	(0.52)		(0.29)	(-1.33)	(-0.72)	(6.60)	(0.33)			
(12) 2009	4.241	0.012	0.063	0.079	0.352	0.020	N/A	-0.137	-6.919	0.863	19.56	22.73	0.088	0.045	0.083
	(6.77)	(1.25)	(17.0)		(3.57)	(0.28)		(-0.78)	(-2.47)	(0.46)	(5.94)	(1.63)			
(13) 2010	2.241	0.021	0.071	0.089	0.329	0.187	N/A	0.531	-8.099	-0.613	22.21	-13.85	0.102	0.041	0.062
	(4.00)	(1.88)	(17.6)		(3.10)	(2.41)		(2.92)	(-3.31)	(-0.37)	(7.93)	(-1.17)			
(14) 2011	2.895	0.041	0.076	0.104	0.093	0.089	N/A	0.538	-2.930	1.947	14.88	-13.41	0.112	0.074	0.101
	(5.77)	(3.57)	(18.3)		(0.87)	(1.12)		(2.67)	(-1.35)	(1.36)	(6.17)	(-1.12)			
(15) 2012	3.466	0.035	0.079	0.110	0.254	0.266	N/A	0.452	-3.762	0.430	18.32	-14.57	0.117	0.056	0.066
	(6.20)	(2.96)	(18.5)		(2.30)	(3.30)		(2.02)	(-1.48)	(0.27)	(6.43)	(-0.96)			
(16) 2013	2.158	0.017	0.067	0.080	0.206	0.102	N/A	0.236	-4.983	1.038	13.80	-2.348	0.085	0.001	0.030
	(4.32)	(1.41)	(15.5)		(1.85)	(1.29)		(1.26)	(-2.17)	(0.73)	(5.32)	(-0.26)			
(17) 2014	1.930	0.014	0.065	0.071	0.231	0.133	N/A	0.549	-4.381	1.347	13.62	-9.114	0.077	0.018	0.052
	(3.87)	(1.15)	(14.5)		(1.90)	(1.48)		(2.53)	(-1.97)	(0.77)	(5.09)	(-0.85)			
(18) 2015	2.040	0.017	0.071	0.086	0.168	0.005	N/A	0.281	-5.895	2.244	12.78	18.43	0.097	0.063	0.120
	(4.01)	(1.46)	(15.8)		(1.40)	(0.06)		(1.15)	(-2.81)	(1.20)	(4.68)	(1.30)			

Table 11: Life Cycles Predicting Investment

The table reports OLS estimates for our sample of annual firm observations from 1997 to 2015. An observation is one firm in one year. The dependent variable is noted in the panel headers and the first column of the table and include R&D/assets and CAPX/assets. Panel A reports results based on our full sample including all firms. Panel B reports results when we limit the sample to manufacturing firms (those with SIC codes between 2000 and 3999). All specifications include firm and year fixed effects. Standard errors are clustered by firm. t-statistics are in parentheses.

Row	Dependent Variable	Life1	Life2	Life3	Life4	TobQ x Life1	TobQ x Life2	TobQ x Life3	TobQ x Life4	Tobins Q	Log Age	Log Assets	Whole 10-K Size	Obs/ Adj R^2
	Panel A: Dependent Variable: Investment Policy (All Firms)													
(1)	R&D/									-0.001	0.000	-0.012	0.000	77,170
	Assets									(-4.64)	(0.01)	(-12.4)	(2.05)	0.862
(2)	R&D/	0.027	0.002	0.000	0.004	0.001	-0.001	-0.004	-0.006		0.000	-0.012	0.000	77,170
	Assets	(4.90)	(0.77)		(0.71)	(0.40)	(-1.08)	(-2.57)	(-1.26)		(0.23)	(-12.6)	(4.17)	0.862
(5)	CAPX/									0.002	-0.007	0.001	0.000	77,170
	Assets									(12.4)	(-5.86)	(2.32)	(0.25)	0.811
(6)	CAPX/	0.026	-0.007	0.000	-0.004	-0.003	0.008	0.003	0.003		-0.007	0.001	0.000	77,170
	Assets	(8.11)	(-1.80)		(-1.07)	(-4.07)	(5.06)	(3.36)	(1.12)		(-5.88)	(2.19)	(1.18)	0.813
	Panel B: Dependent Variable: Investment Policy (Manufacturing Only)													
(3)	R&D/									-0.001	-0.003	-0.022	-0.000	29,841
	Assets									(-2.75)	(-0.63)	(-10.8)	(-0.26)	0.867
(4)	R&D/	0.044	0.017	0.000	0.002	0.002	-0.001	-0.008	-0.007		-0.002	-0.022	0.000	29,841
	Assets	(3.26)	(1.81)		(0.15)	(0.83)	(-0.35)	(-2.40)	(-0.70)		(-0.32)	(-10.9)	(1.68)	0.867
(7)	CAPX/									0.002	-0.010	0.000	-0.000	29,841
	Assets									(9.48)	(-4.95)	(0.62)	(-0.02)	0.755
(8)	CAPX/	0.034	-0.019	0.000	-0.000	-0.007	0.016	0.002	0.003		-0.010	0.000	0.000	29,841
	Assets	(6.50)	(-3.66)		(-0.03)	(-7.81)	(10.3)	(1.19)	(0.60)		(-4.71)	(0.42)	(0.83)	0.759

Table 12: Life Cycles Predicting M&A Transactions

The table reports OLS estimates for our sample of annual firm observations from 1997 to 2015. An observation is one firm in one year. The dependent variable is noted in the panel headers and the first column of the table and include dummy variables indicating whether the firm was an acquirer or a target of an acquisition in the given year. We also consider more stringent versions of these variables where the acquisition was specifically a merger involving the entire firm. Panels A and C report results based on our full sample including all firms. Panels B and D report results when we limit the sample to manufacturing firms (those with SIC codes between 2000 and 3999). All specifications include firm and year fixed effects. Standard errors are clustered by firm. t-statistics are in parentheses.

Row	Dependent Variable	Life1	Life2	Life3	Life4	TobQ x Life1	TobQ x Life2	TobQ x Life3	TobQ x Life4	Tobins Q	Log Age	Log Assets	Whole 10-K Size	Obs/ Adj R^2
	Panel A: Acquirer or Target of any Acquisition (All Firms)													
(1)	Acquirer	0.147	0.007	0.000	-0.187	-0.021	0.026	0.043	0.063		-0.045	0.016	-0.000	77,170
		(4.21)	(0.23)		(-4.53)	(-4.63)	(4.69)	(6.88)	(4.00)		(-3.78)	(3.79)	(-2.88)	0.587
(3)	Target	-0.017	-0.015	0.000	0.147	0.005	-0.008	-0.006	-0.047		0.041	0.038	0.000	77,170
		(-0.63)	(-0.64)		(4.20)	(1.61)	(-2.71)	(-1.49)	(-3.51)		(4.40)	(11.2)	(3.82)	0.447
	Panel B: Acquirer or Target of any Acquisition (Manufacturing Only)													
(2)	Acquirer	0.155	-0.069	0.000	-0.247	-0.035	0.040	0.049	0.110		-0.045	0.036	-0.000	29,841
		(2.44)	(-1.14)		(-3.09)	(-5.00)	(3.52)	(4.60)	(3.66)		(-2.21)	(5.67)	(-2.13)	0.572
(4)	Target	-0.039	-0.036	0.000	0.142	0.006	-0.007	-0.013	-0.055		0.013	0.032	0.000	29,841
		(-0.76)	(-0.76)		(1.87)	(1.21)	(-0.79)	(-1.70)	(-2.45)		(0.83)	(6.14)	(2.58)	0.441
	Panel C: Acquirer or Target of a Complete Merger(All Firms)													
(5)	Acquirer	0.074	0.006	0.000	-0.066	-0.003	0.014	0.021	0.014		-0.022	-0.005	-0.000	77,170
	(Merger)	(3.00)	(0.27)		(-2.49)	(-0.93)	(3.53)	(4.50)	(1.13)		(-2.58)	(-1.66)	(-1.43)	0.343
(7)	Target	0.003	-0.011	0.000	0.042	0.001	-0.002	-0.003	-0.014		0.012	0.005	0.000	77,170
	(Merger)	(0.22)	(-0.82)		(2.11)	(0.58)	(-1.64)	(-1.55)	(-2.03)		(2.43)	(2.86)	(1.89)	0.277
	Panel D: Acquirer or Target of a Complete Merger (Manufacturing Only)													
(6)	Acquirer	0.119	-0.000	0.000	-0.125	-0.017	0.020	0.034	0.047		-0.054	0.006	-0.000	29,841
	(Merger)	(2.81)	(-0.00)		(-2.40)	(-3.68)	(2.55)	(4.01)	(2.09)		(-3.63)	(1.26)	(-1.35)	0.317
(8)	Target	0.018	-0.029	0.000	0.005	-0.002	0.002	-0.006	0.002		-0.005	0.004	0.000	29,841
	(Merger)	(0.64)	(-1.14)		(0.13)	(-0.88)	(0.44)	(-1.56)	(0.14)		(-0.64)	(1.41)	(1.42)	0.250

Table 13: Life Cycles Predicting Outcomes

The table reports OLS estimates for our sample of annual firm observations from 1997 to 2015. An observation is one firm in one year. The dependent variable is noted in the panel headers and the first column of the table and include OI/assets, OI/sales, sales growth and a set of variables indicating whether the focal firm has product offerings that are similar to firms doing IPOs or those receiving venture funding (see Hoberg, Phillips and Prabhala (2014)). We also consider the rate of IPOs in the given firm's TNIC-3 or SIC-3 industry, computed as the fraction of firms in year $t+1$ that are new IPO firms. All RHS variables are ex-ante measurable in year t. Panel A reports results based on our full sample including all firms. Panel B reports results when we limit the sample to manufacturing firms (those with SIC codes between 2000 and 3999). All specifications include firm and year fixed effects. Standard errors are clustered by firm. t-statistics are in parentheses.

Row	Dependent Variable	Life1	Life2	Life3	Life4	TobQ x Life1	TobQ x Life2	TobQ x Life3	TobQ x Life4	Tobins Q	Log Age	Log Assets	Whole 10-K Size	Obs/ Adj R^2
							Panel A: Operating and IPO Outcomes (All Firms)							
(1)	oiassets	-0.007	-0.035	0.000	-0.040	-0.011	0.023	0.012	0.003		0.030	0.002	-0.000	77,170
		(-0.53)	(-2.73)		(-2.55)	(-3.29)	(4.67)	(2.47)	(0.25)		(6.81)	(1.16)	(-7.59)	0.742
(3)	oisales	-0.053	-0.031	0.000	-0.085	-0.019	0.018	0.013	0.004		0.053	0.008	-0.000	77,170
		(-2.55)	(-1.82)		(-3.61)	(-4.07)	(3.91)	(2.24)	(0.26)		(7.26)	(2.50)	(-6.18)	0.776
(5)	Sales	0.066	-0.068	0.000	-0.111	0.037	0.045	0.025	0.119		-0.170	-0.079	0.000	76,906
	Growth	(1.67)	(-2.28)		(-2.59)	(3.89)	(5.86)	(2.09)	(4.06)		(-16.8)	(-15.9)	(5.00)	0.364
(1)	VC Text	1.995	-0.941	0.000	-1.490	-0.031	0.027	0.263	0.320		-0.633	0.508	0.000	69,975
	Simil	(7.19)	(-4.21)		(-4.25)	(-0.91)	(0.97)	(5.83)	(1.99)		(-5.28)	(12.7)	(7.16)	0.979
(3)	IPO Text	1.427	-0.886	0.000	-0.883	0.295	0.065	0.303	0.154		0.181	0.303	0.000	69,975
	Simil	(4.85)	(-3.41)		(-2.80)	(6.55)	(1.09)	(5.10)	(1.00)		(1.53)	(8.08)	(6.05)	0.946
(5)	IPO rate	0.001	0.003	0.000	0.001	0.002	0.000	0.002	0.001		-0.002	0.001	0.000	77,170
	(SIC-3)	(0.67)	(1.77)		(0.34)	(5.72)	(0.19)	(4.93)	(1.21)		(-2.79)	(2.28)	(1.73)	0.563
(7)	IPO rate	0.014	0.004	0.000	0.003	0.005	0.001	0.007	0.003		-0.012	0.000	0.000	74,817
	(TNIC-3)	(3.37)	(1.10)		(0.86)	(5.63)	(1.84)	(6.39)	(1.37)		(-8.53)	(0.15)	(3.67)	0.525
							Panel B: Operating and IPO Outcomes (Manufacturing Only)							
(2)	oiassets	-0.001	-0.092	0.000	-0.010	-0.021	0.040	0.024	-0.015		0.035	0.018	-0.000	29,841
		(-0.04)	(-4.19)		(-0.31)	(-4.15)	(5.67)	(3.41)	(-0.67)		(3.71)	(4.72)	(-3.66)	0.762
(4)	oisales	-0.079	-0.093	0.000	-0.015	-0.028	0.036	0.037	-0.039		0.086	0.026	-0.000	29,841
		(-2.18)	(-3.13)		(-0.36)	(-3.83)	(3.81)	(3.96)	(-1.20)		(6.14)	(4.51)	(-2.56)	0.797
(6)	Sales	0.025	-0.133	0.000	-0.077	0.033	0.068	0.011	0.059		-0.136	-0.084	0.000	29,719
	Growth	(0.32)	(-2.18)		(-0.94)	(2.17)	(3.80)	(0.49)	(1.11)		(-7.35)	(-10.7)	(3.32)	0.337
(2)	VC Text	2.864	-0.094	0.000	-1.516	-0.045	-0.012	0.343	0.167		-0.679	0.632	0.001	27,204
	Simil	(5.72)	(-0.20)		(-2.72)	(-0.91)	(-0.15)	(3.73)	(0.62)		(-3.19)	(9.92)	(4.90)	0.982
(4)	IPO Text	1.438	0.310	0.000	-0.886	0.165	-0.004	0.309	0.049		-0.372	0.227	0.000	27,204
	Simil	(3.03)	(0.68)		(-1.50)	(3.18)	(-0.05)	(2.73)	(0.20)		(-2.03)	(3.97)	(2.67)	0.953
(6)	IPO rate	-0.002	0.004	0.000	-0.000	0.001	-0.000	0.002	0.001		0.004	0.001	0.000	29,841
	(SIC-3)	(-0.65)	(1.33)		(-0.05)	(3.74)	(-0.86)	(2.86)	(0.59)		(3.98)	(2.32)	(1.74)	0.574
(8)	IPO rate	0.010	-0.002	0.000	-0.007	0.001	0.004	0.004	0.006		-0.003	0.001	0.000	28,885
	(TNIC-3)	(1.35)	(-0.27)		(-0.88)	(1.59)	(2.62)	(2.76)	(1.27)		(-1.39)	(1.57)	(2.68)	0.495

Table 14: Tech Bust and Financial Crisis and Life Cycle Transitions

The table reports OLS estimates for our sample of annual firm observations. One observation is one firm in one year. The dependent variable is a firm-specific life cycle variable as noted in the first column. Key is the financial crisis shock (Panel A) or the tech bust shock (Panel B). The treatment year for the tech bust is 2001 and the pre-treatment year is 1999. The treatment year for the tech bust is 2009 and the pre-treatment year is 2007. Note that for each firm, we only include observations from two years, one pre-treatment and one post-treatment. All specifications include firm and year fixed effects. Standard errors are clustered by firm. t-statistics are in parentheses.

Row	Dep. Variable	Life1	Life2	Life3	Life4	ShockX Life1	ShockX Life2	ShockX Life3	ShockX Life4	Log Age	Log Assets	Whole 10-K Size	Tobins Q	Obs/ Adj R^2
	Panel A: Shock is comparison of 2001 to 1999 (tech bust shock)													
(1)	Life1	0.271	0.000	0.000	-0.090	-0.076	-0.000	-0.001	0.014	0.006	0.001	0.000	0.001	11,291
		(11.9)	(0.02)		(-3.61)	(-8.74)	(-0.08)	(-0.11)	(0.57)	(0.58)	(0.35)	(1.76)	(2.27)	0.929
(2)	Life2	-0.028	0.243	0.000	0.032	0.045	-0.031	0.052	0.053	-0.036	-0.000	-0.000	-0.001	11,291
		(-1.17)	(9.82)		(0.64)	(4.93)	(-4.21)	(5.75)	(1.96)	(-2.98)	(-0.09)	(-0.46)	(-1.56)	0.929
(3)	Life3	0.019	0.000	0.208	0.061	0.028	0.014	-0.058	-0.111	0.009	-0.004	-0.000	0.001	11,291
		(0.83)		(9.34)	(1.59)	(3.13)	(2.05)	(-6.24)	(-4.08)	(0.77)	(-1.29)	(-1.78)	(1.26)	0.897
(4)	Life4	-0.055	-0.035	0.000	0.205	0.004	0.018	0.006	0.044	0.020	0.003	0.000	-0.001	11,291
		(-3.39)	(-2.24)		(3.16)	(0.72)	(4.62)	(1.07)	(1.40)	(2.96)	(1.42)	(1.15)	(-2.51)	0.803
(5)	LifeDelist	-0.060	-0.026	0.000	0.015	0.049	0.024	-0.002	0.016	0.099	-0.047	0.000	-0.003	11,291
		(-2.00)	(-0.89)		(0.58)	(3.28)	(2.42)	(-0.15)	(0.60)	(5.40)	(-7.23)	(0.78)	(-2.57)	0.818
	Panel B: Shock is comparison of 2009 to 2007 (financial crisis shock)													
(6)	Life1	0.261	-0.035	0.000	-0.081	-0.051	-0.004	0.013	0.036	0.022	0.002	-0.000	-0.000	7,985
		(10.7)	(-2.16)		(-4.53)	(-6.16)	(-1.10)	(2.00)	(2.61)	(2.13)	(0.82)	(-0.27)	(-0.44)	0.957
(7)	Life2	-0.006	0.285	0.000	-0.021	0.004	-0.007	-0.010	0.116	-0.028	0.001	0.000	-0.001	7,985
		(-0.25)	(10.4)		(-0.58)	(0.44)	(-1.12)	(-1.20)	(4.90)	(-2.16)	(0.36)	(0.67)	(-0.79)	0.956
(8)	Life3	0.007	0.000	0.221	-0.027	0.031	-0.001	-0.012	0.097	0.001	0.004	-0.000	0.002	7,985
		(0.25)		(9.13)	(-1.01)	(3.39)	(-0.26)	(-1.28)	(5.24)	(0.04)	(1.32)	(-2.23)	(2.21)	0.932
(9)	Life4	-0.040	-0.028	0.000	0.349	0.016	0.012	0.008	-0.249	0.005	-0.008	0.000	-0.001	7,985
		(-2.39)	(-1.31)		(9.19)	(2.85)	(3.19)	(1.48)	(-9.76)	(0.53)	(-2.64)	(2.41)	(-1.91)	0.883
(10)	LifeDelist	-0.021	-0.013	0.000	-0.019	0.022	0.011	-0.013	0.020	0.031	-0.020	0.000	-0.005	7,985
		(-0.43)	(-0.35)		(-0.52)	(1.38)	(1.43)	(-1.14)	(0.60)	(1.49)	(-2.37)	(1.55)	(-1.48)	0.738

Table 15: Major Market Disruption Shocks and Life Cycles

The table reports OLS estimates for our sample of annual firm observations. One observation is one firm in one year. The dependent variable is a firm-specific life cycle, acquisition, investment or outcome variable as noted in the first column. Key is the market disruption shock variable and its interaction with ex-ante life cycle stages. In the left-most four columns, the market disruption shock is the average change in (number of 10-K paragraphs mentioning of market disruption)/(number of paragraphs in the firm's 10-K), averaged over distant horizontal peers (TNIC peers who are in a firm's TNIC-2 circle but not its inner TNIC-3 circle). In the right-most four columns, the disruption shock is the average of this same variable over vertically related peers as computed in Fresard, Hoberg, and Phillips (2017). Paragraphs mentioning market disruptions must contain a word having the root "disrupt" and must contain the word "market" or "markets". All RHS variables are ex ante measurable in year $t-1$. Although not displayed to conserve space, all models also include the raw levels of the Life cycle variables, and controls for firm age, firm size, 10-K size, and Tobins' Q. All specifications include firm and year fixed effects. Standard errors are clustered by firm. t-statistics are in parentheses.

	Shock to Distant Horizontal Peers				Shock to Vertical Peers				
Row Dependent Variable	Shock x Life1	Shock x Life2	Shock x Life3	Shock x Life4	Shock x Life1	Shock x Life2	Shock x Life3	Shock x Life4	Obs/ R^2
Panel A: Impact of ex ante shocks on ex post life cycle states									
life1	0.029	4.618	-1.341	-4.333	-0.877	4.645	-5.713	-3.045	75,509
	(0.02)	(4.86)	(-1.02)	(-1.32)	(-0.51)	(4.45)	(-3.54)	(-0.84)	0.851
life2	4.733	2.479	-11.72	6.717	4.459	0.301	-5.584	2.391	75,509
	(2.64)	(2.15)	(-7.78)	(1.61)	(2.23)	(0.23)	(-2.91)	(0.49)	0.856
life3	-6.420	-6.890	15.59	-14.16	-4.521	-4.598	13.86	-13.72	75,509
	(-3.26)	(-5.42)	(9.29)	(-3.08)	(-1.99)	(-3.37)	(5.49)	(-2.65)	0.774
life4	1.659	-0.207	-2.532	11.77	0.939	-0.349	-2.566	14.38	75,509
	(1.68)	(-0.31)	(-3.25)	(2.85)	(0.91)	(-0.51)	(-2.74)	(3.48)	0.659
Panel B: Impact of ex ante shocks on ex post investment									
R&D/	-4.704	3.738	2.678	3.297	0.020	0.309	0.125	3.219	75,509
Assets	(-1.97)	(4.03)	(1.88)	(1.44)	(0.01)	(0.38)	(0.08)	(1.23)	0.840
CAPX/	-2.387	-1.258	5.820	6.305	-2.704	-2.338	4.435	8.885	75,509
Assets	(-2.43)	(-1.30)	(8.16)	(3.26)	(-2.30)	(-1.94)	(4.45)	(2.98)	0.708
Acquirer	4.887	-9.726	-15.05	-50.25	14.36	-4.567	-17.90	-92.36	75,509
	(0.45)	(-1.26)	(-1.66)	(-2.13)	(1.20)	(-0.58)	(-1.61)	(-3.24)	0.375
Target	2.181	23.86	-10.47	-38.71	0.596	15.93	-17.36	-49.01	75,509
	(0.26)	(3.63)	(-1.45)	(-1.78)	(0.06)	(2.29)	(-1.84)	(-1.80)	0.321
Acquirer	-15.17	2.624	-7.893	-24.76	-7.089	8.973	-0.378	-38.72	75,509
(Merger)	(-1.89)	(0.48)	(-1.15)	(-1.47)	(-0.83)	(1.62)	(-0.04)	(-1.77)	0.253
Target	-12.46	4.956	-3.511	2.768	-4.119	4.813	-8.308	-3.520	75,509
(Merger)	(-2.64)	(1.33)	(-0.82)	(0.22)	(-0.68)	(1.24)	(-1.58)	(-0.21)	0.244
Panel C: Impact of ex ante shocks on ex post outcomes									
oiassets	22.50	-28.49	-3.971	2.197	22.04	-22.94	5.766	-1.994	75,509
	(4.78)	(-8.48)	(-1.42)	(0.35)	(4.38)	(-6.28)	(1.75)	(-0.23)	0.733
oisales	43.53	-69.78	-31.99	-8.547	45.06	-44.26	7.276	10.91	75,509
	(5.73)	(-11.6)	(-5.68)	(-0.69)	(5.88)	(-6.13)	(1.28)	(0.79)	0.767
Sales	19.33	-41.13	19.90	-42.90	38.91	-37.89	20.00	-64.67	75,279
Growth	(1.72)	(-6.35)	(2.89)	(-2.13)	(3.68)	(-5.95)	(2.59)	(-3.06)	0.320
tsimm	688.25	153.96	-2775.9	-982.43	855.67	425.30	-2178.4	-93.63	75,344
	(2.81)	(1.24)	(-10.1)	(-2.17)	(3.95)	(3.67)	(-7.94)	(-0.17)	0.927

Figure 1: Mean values of Life1 to Life4 for firms in the bottom and top quartiles of firms by asset size, computed annually.

Figure 2: Average Firm Dynamism index, which is defined as $log[\frac{Life1+Life2+Life4}{Life3}]$, for firms in the bottom and top quartiles of firms by asset size, computed annually.

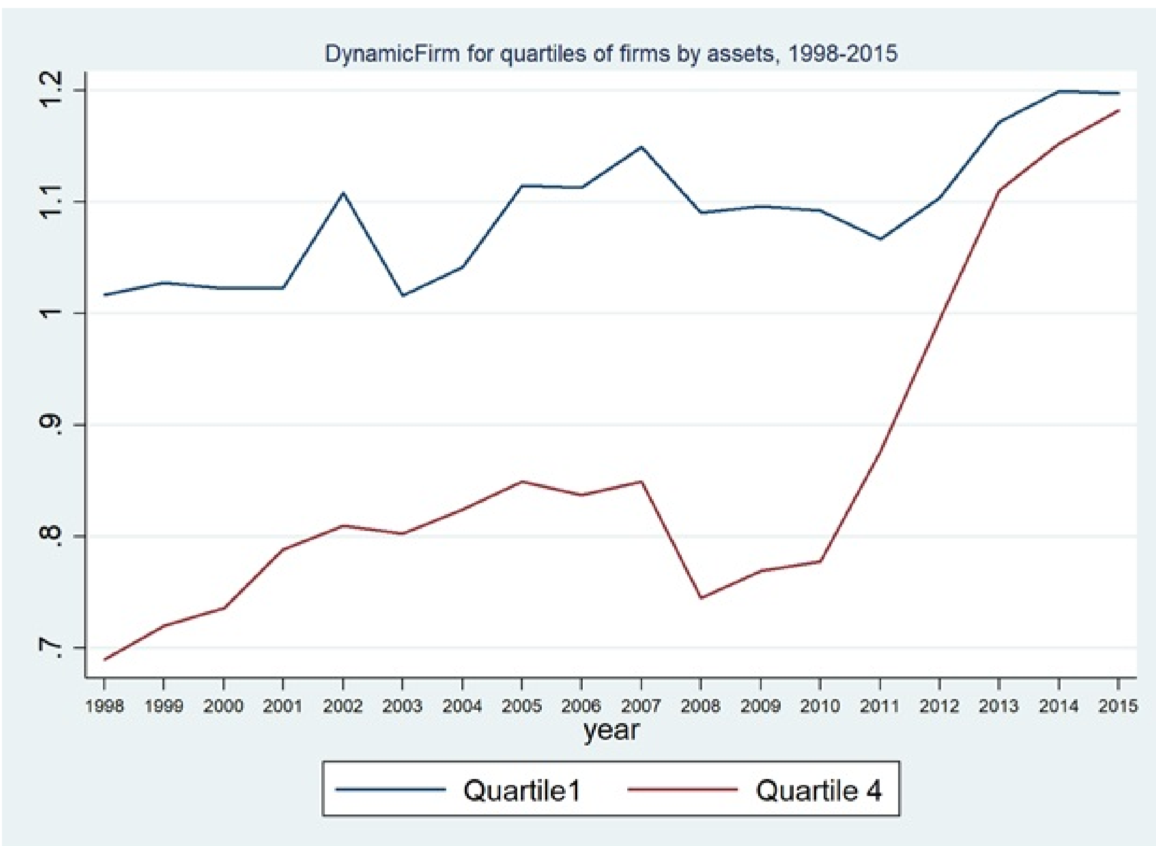
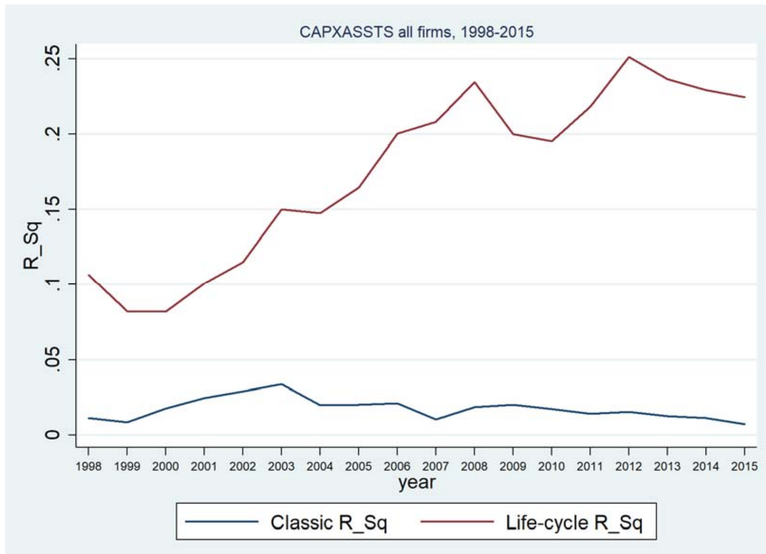


Figure 3: Plot of the R^2 of the annual cross sectional regressions in Tables 7 and 8. The Basic Classic model does not adjust for differences in the investment-Q relationship for different values of the life variables. The Conditional model adjusts for the level of the Life variables and their interaction with Tobin's Q.

Panel A – CAPX/Assets



Panel B – R&D/Assets