Product Life Cycles in Corporate Finance

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ABSTRACT

We show that large US public corporations have undergone a significant change in recent years, becoming more entrepreneurial and diversified across product life cycle stages. This diversification improves the intensity and stability of internal capital markets and reduces the need to raise external capital to fund innovation. Motivated by theory, we measure each firm's exposure to four life cycle stages, and introduce a novel conditional investment-Q model. The new model improves the explanatory power of baseline models by a full order of magnitude, produces Q-sensitivities that are 3-7x larger, and explains recent puzzles including claims that investment and issuance Q-sensitivities are declining over time. Central to these conclusions, we document that many firms are shifting away from the less active mature product life cycle state and are thus becoming more entrepreneurial, dynamic and diversified across the states. Shocks to international competition and growth options likely explain much of this shift toward dynamism.

1 Introduction

The early years of the 21st century have seen substantial changes in the characteristics and the composition of U.S. pubic firms. The number of public firms has declined steeply, and these firms have less fixed capital, they spend more on research and development than on capital expenditures, and they are larger and older.[1] At the same time, there have been major changes in how public firms use public and private financial markets, increases in market concentration and the creation of superstar firms.[2] These developments are at the heart of understanding the investment and financing decisions of firms.

In this paper, we document a major shift in U.S. corporations that is entirely new to the literature. In particular, we measure firm-level changes in exposure to product life cycle stages, and we then link these exposures to financing and investment decisions. During our sample period from 1998-2015, large numbers of firms abandoned the mature stage of the life cycle in favor of the other more diversified and dynamic product market strategies. We refer to this trend, which is remarkably stronger for large firms, as the "Rise of the Dynamic Firm". We find that increases in dynamism interact with increases in market power, which then affect investment (CAPX, R&D, and acquisitions) and external financing in highly competitive and less competitive markets differently. These findings can explain several anomalies in the financing and investment literatures.

To analyze these issues, we develop a novel 10-K text-based model of firm life-cycles that relates theoretically to the firm's portfolio of growth opportunities. We use this measure alongside an existing network-relatedness measure of competition and analyze how firms issue securities and invest. We extend the standard empirical model of investment and financing of growth opportunities using Q-theory, the idea

[1] See Doidge, Kahle, Karolyi and Stulz (2018). They show that fixed assets have fallen from 34% to 20% of total assets between 1975 and 2016. Average capital expenditures had fallen to just about half annual R&D expenses.

[2] See for example, the Council of Economic Advisors (2016) Issue Brief on "Benefits of Competition and Indicators of Market Power," Autor et al (2017), Bloom (2017), Lee, Shin and Stulz (2016), Grullon, Larkin, and Michaely (2016), and Gutierrez and Phillipon (2016).

that firms invest until the present value of marginal cash flows exceeds the cost of investment. Overall, we obtain five principal results.

First, we show that over our sample period (1998-2015), large mature firms in the U.S. have become more entrepreneurial. This diversification across life cycle stages indicates that large firms are becoming more engaged in developing products in early life cycle states. As a result, they are investing more in research and development, and unlike baseline investment-Q models, our life cycle enhanced investment-Q model has increasing explanatory power over time. Our main result on the financing side arises as a related consequence. Large firms package cash-flow-negative entrepreneurial product investments alongside cash-flow-positive mature product lines, all within a single firm's boundaries. This creates diversification of external financing needs, and hence a reduction in the aggregate requirement for external capital market funding, especially for high-Q investment opportunities. Once these firm-level compositional changes are factored in, and we employ the enhanced investment-Q model, the puzzle identified by Doidge et al (2018) that public funding does not flow to high-Q firms is explained, and a normal relationship between Q and external capital financing is restored.

Second, we show that conditioning on firm exposures to life-cycle states dramatically improves the performance of investment-Q models and resolves the apparent empirical weakening ability of Q models to explain capital expenditures over time. For example, Lee, Shin and Stulz (2016) and Gutierrez and Phillipon (2016) document major declines in the explanatory power of Tobin's Q as conventionally measured to explain capital expenditures since 2002. For brevity, we henceforth refer to adjusted R^2 as just R^2. We confirm this in our sample as the adjusted R^2 of the Q-model declines from 3.3% to 0.6% from 2003 to 2015, a more than 80% decline. However, once we condition the Q-model on life-cycle stages, the R^2 of the conditional model is not only an order of magnitude higher overall, it also *increases* strongly over time. This rise in R^2 is particularly stark as R^2 rises from 10.5% to 22.2% during our sample period from 1998 to 2015.

Third, we show that our text-based product life cycle model well-describes how firm investment and focus evolve as a firm's products advance in the life cycle. In addition to the aforementioned predictions, our results also support the following regarding investment, mergers and acquisitions, issuance, and outcomes. Firms in the product innovation stage invest heavily in R&D, and they invest even more intensively when their market valuations rise. These entrepreneurial investments are often equity-financed, as equity issuance is also sensitive to Q for these firms. In contrast, firms focused on the process innovation stage of the life cycle, and more mature firms, invest heavily in CAPX, and both CAPX and debt financing are sensitive to Tobins' Q.

Also regarding investment, we find strong results for mergers and acquisitions. Our results indicate that the most 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 that have internal growth options, tend to be the acquirers. Hence there is a broad pattern of asset transfer from late stage firms to firms that are in the more youthful stages. This is consistent with elderly firms delivering value to their shareholders by selling assets to more youthful firms, who have the capacity to pay premia for assets that can fuel their growth. Interestingly, when declining firms experience rising market values, these firms switch from targets selling assets to acquirers buying assets, consistent with declining firms making risky bets in an attempt to transition to more youthful stages of the life cycle. Our results support this intuition as firms in decline with high Q are indeed somewhat likely to transition toward earlier and more youthful stages of the life cycle ex post. These results illustrate that although the life cycle progresses from youthful to elderly on average, elderly firms can become young again following shocks or risky bets to reignite growth.

Fourth, we show that the level of competition also matters in understanding how firms with different exposures to the product life cycle respond to investment and financing opportunities. Broadly, in competitive markets, firms that are more dynamic (those focused on product and process innovation) respond most strongly to Q in the manner described above. However, novel strategies for firms in less competitive markets also emerge. When firms have increased exposure to declining products, we also find that the R&D and acquisition investments of dynamic firms are very sensitive to Q. This is in contrast to similar firms in competitive industries. This finding suggests that firms facing lower competition have the luxury of being more opportunistic and patient when faced with obsolescence. These firms can time their shifts toward new product innovation spending or the purchase synergistic assets to align well with any positive shocks to their growth opportunities.

Our fifth contribution is to show that market shocks, such as global competition, the financial crisis, and the technology bust, lead to changes in firm life cycle stages. Following the technology bust of 2000 to 2002, we find that firms in the more innovative life cycle stages transition 1-2 stages toward less active stages. Many firms with an ex ante focus on product innovation transition to maturity, and some transition to delisting. Firms focused on the process innovation stage transition to maturity, decline, and delisting. We find similar patterns for the financial crisis period where firms also make dramatic transitions from early stages to later stages of the cycle. Because we also find that life cycle exposures are sticky, these results suggest that there are potentially important long term consequences of major shocks, as they can impair the innovative product strategies for prolonged periods.

Globalization, as measured by firm mentions of international competition and international growth opportunities in their 10-K, also has a strong effect on firm life cycle stages. In particular, both competition and opportunities are associated with increases in the youthful product innovation stage. These effects persist and remain significant even when we instrument own-firm international competition and growth options using shocks to each firm's competitors, or to the competitors of the firm's competitors (thus focusing on more exogenous shocks to markets where the firm does not compete directly).

Our approach is based on textual analysis of 10-Ks using anchor-phrase methods used in prior studies such as Hoberg and Maksimovic (2015) and Hoberg and Moon (2017). We use the four-stage life cycle depicted in Abernathy and Utterback (1978) to identify direct statements in firm 10-Ks that indicate product life cycle stages. We bin these phrases into four groups that correspond to each of the aforementioned four stages in the Abernathy and Utterback (1978) life cycle (product innovation, process innovation, maturity, decline). Each firm is then is then mapped to a four element vector in each year, with vector components that sum to one, each element indicating the fraction of the firm's direct statements that correspond to each of the four life cycle stages. Because firms have product portfolios that can include multiple products in different life cycle stages, our approach thus allows us to capture the full richness of each firm's overall product portfolio using continuous distributional measures. Most firms indeed have 4-element vectors that have mass in more than one stage of the life cycle. This further allows us to measure the unique impact of each of the four life cycle stages on ex post investment strategies and outcomes.

We validate our life cycle model by looking at the relation 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).

The novel investment and acquisition patterns we find are not possible to observe using simple life cycle proxies such as firm age, which do not contain adequate dimensionality to fully observe shifts in investment opportunities across life cycle stages. We find rigorous support for this statement by constructing a four-stage alternative life cycle based on sorting firms into age-based quartiles. This alternative model is not informative, whereas the direct text-based measures are highly informative. Moreover, the informativeness of firm age is limited by the fact that life cycle transitions have a stochastic component. For example, we find that some shocks can accelerate the aging process. In other cases, shocks can induce firms to transition back toward more youthful life cycle states. Because our results cannot be obtained using age alone, our findings are novel relative to the existing literature.

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 have important ramifications for research on innovation, growth opportunities, firm organization, and the competitiveness of various product markets.

2 Overview and Related Literature

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 changes. 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 ramping up production while supporting the products still 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.

While the stages of the product life cycle drive investment decisions directly, there is a parallel relation for financing policies. For example, the design and development are likely to be financed with equity. As the firm progresses to investing in process innovation, including investments in tangible assets such as plants and distribution channels, it becomes more likely to issue debt securities, particularly because the tangible assets can be used as collateral. As the project then moves into a mature phase and generates stable cash flows, the tradeoff increasingly favors tax management. Thus, we expect that firm life-cycle stages and the expected growth opportunities available at each stage, will be important predictors of financing.

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, life cycles, 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.[3] 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. Arikan and Stulz (2016) show how firms' acquisition activity follows a U-shaped pattern with respect to age. DeAngelo, DeAngelo and Stulz (2010) find some evidence of life cycle effects in the issuance of equity, but also find that cash shortfalls loom larger. We find many results that are consistent with these studies: age is relevant empirically and we find life cycle effects in many corporate policies. We also find that issuance and investment results often appear together, reinforcing the need for cash as a key issuance motive. However, our results further suggest that a comprehensive model of product life cycles, aggregated to the firm level, generates many novel and economically large findings. In particular, almost all of our five key findings reported earlier are new to the literature.

Much of the empirical analysis analyzing firm investment decisions is based on the Q-theory of investment, worked out by Hayashi (1982). This theory predicts that the firm's investment opportunities can be measured by the ratio of the firm's market value to that of the firm's assets.[4] The Q-theory model has been widely use in Finance, both in structural models, such as Hennessy, Levy, and Whited (2007), and

[3] Maksimovic and Phillips-2008 (2008) explore how industry life-cycles affect capital expenditures.

[4] See Hassett and Hubbard (1997), Caballero (1999) and Philippon (2009) for reviews of the literature.

in numerous reduced-form contexts, such as Chen and Chen (2012), Erickson and Whited (2000), and Harford (2007). 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 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.[5] 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).[6] Using Census data, Magyari (2017) shows that US firms exposed to Chinese import competition shift resources into R&D and service production . There is also evidence that the recent increase in inequality between firms 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.

More broadly, there is recent literature that focuses on how management characteristics affect firm performance. Bertrand and Schoar (2003), Prez-Gonzlez (2006), Bennedsen et al. (2007), Malmendier, Tate, and Yan (2011) and Levine and Rubinstein (2017), among others, focus on the importance of managerial styles for a firms decisions and performance. Also related, Bloom and Van Reenen (2007, 2010), Bloom et. al. (2013) explore how heterogeneity in management practices affect firm growth and productivity differences across countries. Our paper complements this analysis by showing that heterogeneity in firm life-cycle stages leads to different

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

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

investment outcomes.

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 perspective is that the technology contains pre-built modules for fast and highly flexible querying, while producing output that is easy to interpret.[7] 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.

[7]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.

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 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 Measure of competitive interactions between firms

Our primary objective is to study product life cycles, and hence we consider the textual network industry classification developed in Hoberg and Phillips (2016), as this classification is based directly on identifying rivals through their use of related product market text. There are three benefits: (1) the TNIC network is intransitive and hence customized to each firm, (2) it is more informative, and (3) it is dynamic in time. In contrast, concentration ratios using Herfindahl indices based on SIC or NAICS codes are rather static over time given these industry definitions are held constant, and they are calculated using predefined transitive industries (thus ignoring relatedness across groups). They are also backward looking as they use already-realized sales from financial statements.

To compute our firm-specific measure of competition, we first note that TNIC can be expressed as a network where each pair of firms has a known degree of connectedness. We thus follow Hoberg and Phillips (2016) and compute the total product similarity between a given firm and all of its rivals. We use the baseline TNIC-3 classification to identify rivals (this classification is calibrated to be as granular as three-digit SIC codes). As this network provides us with the set of all rivals that are in each focal firm's market, along with the pairwise similarity between each pair of firms, total similarity is simply the sum of pairwise similarities between the focal firm and all of its TNIC-3 rivals.

The resulting network crowdedness measure computes competitive intensity in a focal firm's market as a whole. A firm with low total similarity rarely encounters a competitor in its local area of the product market network. A firm with a high total similarity frequently encounters its competitors. Low total similarity therefore indicates low competition and monopoly-like rents, and high total similarity indicates intense competition with many direct (highly similar) rivals. The micro foundation for product-similarity based competition obtains from the seminal literature on product differentiation dating back to Chamberlin (1933) and Hotelling (1929). The resulting network crowdedness measure computes competitive intensity in a focal firm's market as a whole. A firm with low total similarity rarely encounters a competitor in its local area of the product market network. A firm with a high total similarity frequently encounters its competitors. Low total similarity therefore indicates low competition and monopoly-like rents, and high total similarity indicates intense competition with many direct (highly similar) rivals. The micro foundation for product-similarity based competition obtains from the seminal literature on product differentiation dating back to Chamberlin (1933) and Hotelling (1929). Although we report results using total similarity, we also note that using HHIs generates similar results, which are still highly significant although slightly weaker.

3.4 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 variable in Compustat) is missing, we assume it to be zero. All variables constructed as accounting ratios are winsorized within each year at the 1%/99% level. We use data from SDC Platinum to identify acquirers and targets of acqusitions. Our broad acquisition measure identifies any acquisitions that transact either part or all of the assets from the target firm to the acquirer. We separately consider a measure of mergers that only includes complete acquisitions of the target. We compute Tobins' Q following Gutierrez and Philippon (2017) as the market value of the firm divided by book assets.

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.

3.5 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 in our sample 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%.

Panel A of 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.

Panel B of Table 2 reports the autoregressive coefficients of the four life cycle variables. All four states are roughly 80% persistent, with Life4 being least persistent at 76.4%. These results indicate that a firm's life cycle state vector is stable over time and that firms move through the cycle at a slow speed.

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 heightened 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 profitability) and measures of globalization (text-based intensities of offshore sales and offshore purchases 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 and market power. Profitability (OI/assets) moves from 7.9% to 11.5%, which is also 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 having links to increased market power, but only for larger firms. This is likely because smaller firms do not have the depth of resources and knowledge to implement a more complex dynamic 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 having links to increased market power and globalization. They 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. Dynamism among larger firms can thus offer superior protection from potential entrants, as even the most innovative entrants would still need to out-innovate these deep pocketed incumbents who also have a strong focus on innovation.

4 Validation

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.

5 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 ex ante life cycle variables. We use the same panel data specification as in Table 8 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 6 Here**]

Table 6 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 6 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 Funding and Investment

As shown by Lee, Shin, and Stulz (2016) and Doidge et al. (2018), funds in the U.S. securities markets no longer flow to high-Q industries.[8] We investigate the extent to which we can trace this development to product-cycle changes at the individual firm level.

In Table 7 we regress equity and debt issuances on our model determinants using

[8] Lee, Shin, and Stulz (2016) and Doidge et al. (2018) class firms into Fama-French 44 industries.

OLS panel data regressions from 1997 to 2015 that include firm and year fixed effects, and standard errors are clustered by firm. The dependent variable is ex post equity issuance/assets or debt issuance/assets in year $t+1$. All RHS variables are ex ante observable in year t. The first block of four columns reports results for the basic investment-Q regression that include Tobins' Q and basic controls. The last block of 11 columns is the conditional model, where issuances are regressed on the life variables and their cross terms with Tobins Q.

In each panel, we present results for both value-weighted and equally weighted equity and debt issuances, each in sets of three. In each set, the top equation reports the results on for the full sample, the second reports results for firms whose dynamism exceeds the median, and the last for firms whose dynamism is below the median. Median breakpoints are based on annual sorts in the ex ante year t.

[**Insert Table 7 Here**]

The results for the basic model yield the expected result that high ex ante Q predicts more ex post securities issuance. This also holds across the subsamples, and remains robust for both equity and debt issuance. Moreover, the coefficient on Q in the basic model is similar for the high and low dynamism subsamples. As expected, since equity issuance is more prevalent for smaller firms and debt issuance is more prevalent for larger firms, we find that the fit is better for equally weighted samples in the equity case and value weighted samples in the debt case. The contrast between our firm-level results and the industry-level results in Lee, Shin, and Stulz (2016) and Doidge et al. (2018) is due to our focus on equity issuance alone, whereas Lee eat al focus on equity issuance net of repurchases. The results also differ because they focus on Fama-French-49 industry panel data tests where as we focus on firm level tests.

Turning to the conditional model, many novel insights emerge regarding which firms issue securities. Row (1) in Panel A shows that the relation between equity issuance and Q is driven by the firm's product portfolio exposures specifically to

Life1 and Life2. In contrast, equity issuance Q-sensitivity in the full sample is not responsive to Life3 and Life4 exposures. However, rows (2) and (3) indicate that the sensitivity of equity issuance to Q is only relevant in the dynamic firm subsample. Static firms, which have high loadings on Life3 in row (3), do not increase equity issuance as Q increases.

Inspection of row (2) illustrates a novel pattern, which underscores a main result of our paper. When dynamic firms load highly on life 1, they increase equity issuance when Q rises. However, the more they load on life3, they significantly decrease their equity issuances when Q rises. Thus, as dynamism rises among the large firms during our sample, as shown in Figures 1 and 2 above, these large firms, which historically have higher exposures to life3 due to their maturity, experience de novo increases in Life 1. The consequence is that mature life3 products serve as a hedge to equity issuance. Large firms package cash-flow-negative entrepreneurial product investments alongside cash-flow-positive mature product lines, all within a single firm's boundaries. This creates diversification of external financing needs, and hence a reduction in the aggregate requirement for external capital market funding, especially for high value investment opportunities. Given the high costs of equity issuance (both informational costs and transaction costs), this hedge is likely quite valuable, particularly in periods of increased distress.

Panel B displays the same specification for the equal weighted sample. Once again, the sensitivity of issuance to Q increases with Life1 and Life2 in all specifications. Interestingly, however, we no longer find a significant interaction between Life3 and Q, which is thus in contrast to Panel A. This suggests that the equity financing hedge, related to diversification within the product life cycle, is a large-firm phenomenon. Panel B also shows a significant positive interaction between Life4 and Q, both in the full sample and in the dynamic subsample. This is consistent with smaller firms seeking investments to survive as their portfolios are becoming more obsolete. We show later in this section the these firms use the proceeds for more mature investments such as acquisitions, which also be indicative of potential agency conflicts. We discuss the strategies of life4 firms more later in this section.

Panels C and D show analogous results for debt issuances. The basic model shows a positive relation between Q and debt issuance. The conditional model shows that this relation is entirely due to firms exposed to life2. Thus, debt issuance is particularly sensitive to process innovation, where the focus is often on tangible assets. This is consistent with the usage of debt coinciding with the increased availability of collateral and lower risk growth opportunities.

Next, we perform a similar analysis on the investment side, addressing R&D/Assets, CAPX/Assets and Acquisition/Assets in Table 8. As before, we show both the equally weighted and the value weighted specifications. The first three columns show the basic model, and the remaining columns show the conditional model.

[**Insert Table 8 Here**]

As in the case of issuances, the basic model shows a positive and significant relation between all of the investment outcomes and Q. Again, the conditional model breaks this down into product life-cycle components. As expected, rows (1) and (2) show a very strong positive relation between R&D and Life1 interacted with Q. The the Life4 X Q coefficient in the weighted specification in row (1) is significant and positive, whereas as in the equally weighted test the Life3 X Q coefficient is negative and significant. This is consistent with large high Q firms with heavy Life4 exposures attempting to develop new growth options to escape their declining state and obsolescence. For smaller firms, those in stable life3 markets are likely to reduce R&D as their products mature.

Panels C and D explore the sensitivity of CAPX to Q using a value weighted and equally weighted specification, respectively. As before, the basic model shows a positive and significant relation. The conditional model shows that the positive relation is primarily due to firms having Life2 exposures. There is also evidence of a smaller life3 sensitivity to CAPX – firms with exposure to mature products thus also increase their CAPX when their market valuation is high, presumably to increase production in response to positive demand shocks.

Panels E and F explore the sensitivity of acquisitions to Q using analogous value weighted and equally weighted specifications. Once again, the basic model shows a positive and significant relation. The value weighted conditional model in Panel E shows that the positive relation is primarily due to Life2 exposures, and suggests that large firms likely acquire assets at these times due to efficiency motives. The equal weighted results for acquisitions in Panel F show that smaller firms have acquisition strategies that are very strongly related to the product life cycle. Broadly, earlier stage small firms very strongly avoid acquisitions when their Q is high, presumably to focus exclusively on their high value internal growth options. However, when small firms have elevated Q in all three of the later stages, they become more likely to acquire. This suggests that growth by acquisition is a major component of small firm investment strategies as they age.

Table 9 further investigates the Q-sensitivities of both our funding and investment variables in more refined subsamples. We consider four subsamples formed by yearly unconditional sorts on dynamism and competition. We define dynamism as before, and we define competition as the firm's TNIC total similarity from Hoberg and Phillips (2016). This measure is high when a firm has many rivals in its local markets offering similar products. Hence the measure captures both the existence of many rivals as well as their degree of overlap. We use this measure of competition because, unlike HHIs, it is not reliant on backward-looking accounting performance such as sales. Rather, it is based on the firm's forward looking summary of its businesses, and is scale-invariant. Given our focus on innovation and investment in the future, we feel this distinction is important as firms in such markets often have very low or even on-existent sales. Within each of the four subsamples, we rerun the value weighted conditional model used above, and we report results only for the four life cycle Q-sensitivity terms for parsimony. However, we note that the life cycle level variables, as well as the size and age controls, and the firm and year fixed effects are still included in these subsample regressions but are not displayed.

[**Insert Table 9 Here**]

Panels A and B of Table 9 report the sensitivities of equity and debt issuance to Q when interacted with each of the four life variables. As shown in Table 7, we find that significant sensitivities are mainly observed for dynamic firms. However, we now see that the effects are further localized among firms facing high competition. Issuances in static and less competitive markets, in contrast, are generally unresponsive to Q. The only exception is that firms with exposure to Life4 are likely to issue debt when Q is higher. Panels C to D show that these firms also increase their R&D, CAPX and Acquisitions when Q increases, indicating the use of funds. We find little evidence that funding of firms in static industries respond to Q.

When we turn our attention to investment Q-sensitivities in Panels C, D, and E. We again find strong investment Q-sensitivities in the Dynamic and Competitive Subsample. R&D is sensitive to Q for higher life1 exposures, and CAPX and acquisitions are more sensitive in the presence of higher life2 exposures. Regarding the life4 exposures in the dynamic and low competition subsample, the aforementioned sensitivity to debt financing is associated with corresponding sensitivity to R&D and Acquisitions. Because all tests in this table are value weighted, this suggests that larger firms attempt to escape obsolescence by issuing debt to invest in de novo R&D (presumably to rebuild early stage product exposures) and also to purchase assets through acquisitions.

Several differences between the Dynamic high and low competition subamples are also worth pointing out. First, consistent with Gutierrez and Phillipon (2016), we find far greater sensitivity and thus reactiveness in the high competition subsamples. Firms in less competitive markets are less reactive. However, our results also show that the degree of exposure to dynamic and static life cycles also plays an important role. For example, high competition does not stimulate Q-sensitivity in mature static firms. These firms apparently have few growth options and thus have few options to escape competition. Analogously, low competition firms are particularly non-reactive when their markets are also static and mature. Presumably, these firms are primarily interested in payouts and profits.

Overall, we find that Dynamic and Static firms react differently to Q. Within the Dynamic firm subsample, firms facing high versus low competition also behave differently indicating that both dimensions are independently informative. Dynamic firms in competitive markets are by far the most responsive to Q on almost all dimensions, and particularly in the more innovative stages of the product life cycle where we expect to observe high sensitivities. Yet a particularly novel finding, not reported in the existing literature, is that firms exposed to product obsolescence also become more sensitive to Q, bu this time primarily in dynamic low competition markets. This finding suggests that firms facing low competition indeed are focused primarily on preserving their high rents moreso than they are focused on innovating. Yet when threatened by obsolescence, inaction becomes unpalatable as their very presence might be threatened. In these cases, these firms in less competitive markets seek opportunistic investments (of almost any kind, but especially R&D and acquisitions) when their Q increases.

6.1 Economic Magnitudes

In this section, we report the economic magnitudes of our key findings above. We first note that our extended Q-model is a complete conditional model, and it has fitted coefficients both regarding conditional intercepts and conditional sensitivities to Q. Hence, we report economic magnitudes both regarding investment and issuance policy levels in various subsamples (conditional intercept effects), and also regarding shifts in these policies when Q becomes high or low (conditional sensitivity effects). We focus on five samples: the full sample, four subsamples based on independent yearly sorts dividing the sample by our dynamism score and by competition into four bins: dynamic and competitive, dynamic and low competition, static and competitive, and static and low competition. This allows us to integrate findings regarding life cycles with findings in existing studies regarding competition in this setting.

For each of the five policy variables of interest, we first report their subsample means. We remind readers that all policy variables are based on current year t investment and issuance, and are scaled by beginning-of-period assets following the convention in Lee, Shin and Stulz (2016). Furthermore, all variables used to form sorts and to compute predicted values (including life cycle stages and Tobins' Q) are ex-ante measurable in year $t-1$. The subsample means are important as they indicate the economic magnitude of the conditional intercepts, at least on the dimensions of dynamism and competition.

[**Insert Table 10 Here**]

Table 10 reports the results. The first major finding is that dynamism and competition are both important in predicting where firms are most actively investing and issuing. For three of the five policy variables, the dynamic and high competition subsample is most active. For equity issuance, R&D, and CAPX, the sample wide averages increase from 0.059, 0.051, and 0.047 in the full sample, respectively, to 0.109, 0.071, and 0.101 in the dynamic and competitive subsample. These increases are large, and these activities nearly double for some policies. The joint relevance of life cycles and competition in creating such highly active firms relates to the prediction in Abernathy and Utterback (1978) that the early "fluid" stage of the product life cycle will be characterized by high levels of innovation spending and also high competition. This also relates to the "escape competition" hypothesis discussed in Aghion et al (2005).

Table 10 shows that activity levels for debt issuance and acquisitions are fundamentally different, and are higher in less competitive and more static markets. For example, the full sample averages of 0.121 and 0.031 for debt issuance and acquisitions, respectively, increase to 0.138 and 0.045 in the static and low competition subsample. Yet the raw magnitude of these shifts are more modest. This is due in part to the fact that variation is overall lower for firms in these samples, and hence shifts of this magnitude are still relevant. The conclusion is that acquisitions become more relevant for firms exposed to later stages of the product life cycle, as inorganic growth (generally seen as less profitable) thus becomes more relevant as the firm exhausts its internal growth opportunities. Regarding debt, these more static firms have less operating leverage and risk, and a greater focus on tax management. Hence they are more willing to take on debt to finance acquisitions. The use of debt to fund lumpy and yet transitory investment such as acquisitions is consistent with the exercise of embedded options built into corporate leverage policies (see DeAngelo, DeAngelo and Whited (2011)).

6.1.1 Sensitivity to Tobins Q

The remainder of Table 10 is devoted to examining the sensitivity of the five policies we consider to Tobins' Q. The next three columns report the 25th percentile, median, and 75th percentile levels of Tobins Q in each sample. These statistics vary by sample, but of course do not vary based on which policy is being examined. The main observation is that Q is highest for the dynamic and competitive firms, consistent with these firms indeed being in more entrepreneurial markets, where market valuations are driven primarily by growth options. However, also interesting is the fact that the lowest Q's are not in the diametrically opposite subsample, static and low competition. Rather, Q is lowest in the the static and competitive market. Intuitively, this finding illustrates the role of competition in reducing firm valuations when the firm runs out of growth opportunities. A firm in a static market with high competition likely has little pricing power, and also few opportunities to escape competition. The median Q in these markets is very low at 0.686. In contrast, Q is roughly double in the dynamic and competitive market, with both low competition markets lying in between.

The next 8 columns report the conditional sensitivities of each policy to Tobins Q in each subsample. The methodology is to use the regressions from Table 9 (and the full sample results from the preceding two tables) to compute predicted values of the five policies when we hold all variables to their sample wide means, but shift

Tobins' Q from the 25th percentile to the 75th percentile. If the predicted value of the given policy increases materially, we would conclude that the policy is highly sensitive to Q and the table reports the economic magnitude. We note that these tests are conservative, as the models used to compute the predicted values include firm and year fixed effects in addition to our controls. We further note that these regressions are also value weighted, and hence our economic magnitudes are particularly conservative because larger firms typically have stickier corporate policies. We note that, in unreported tests, that the economic magnitudes are substantially larger if we instead use equal weighted regressions to compute the predicted values. Given these particulars, we believe that our estimates of economic magnitudes are particularly large.

Our main results regarding equity financing are very strong in economic terms. For example, per unit of exposure to life1, the firm's equity issuance shifts from 0.085 when its Q is at the 25th percentile, to a much larger 0.149 when its Q is in the 75th percentile. This intuitive result indicates that firms in this sample issue more equity when their market values rise. This is sensible, as row 17 shows that these same firms increase their investment in R&D from 0.085 to 0.124, which is also economically large. Hence the elevated Q's appear to inspire increased innovation spending that is funded by equity. This finding is likely not surprising, however, the corresponding results for life3 illustrate a novel contribution. Per unit of life3, these same firms greatly reduce their equity issuance from 0.125 to 0.036. This finding is very large in economic terms and suggests that mature products serve as a hedge against the need to issue equity when growth options are particularly good. By bundling mature products and innovative products into the same firm portfolios, firms thus move a step closer to full self-funding, which in turn can reduce dilution and both transaction costs and information costs of equity issuance. Underscoring this interpretation, row 17 shows that R&D spending is much less sensitive to Q per unit of life3 (R&D only drops form 0.096 to 0.082 when Q increases to the 75th percentile). Indeed, Table 9 shows that the relationship between R&D and Q is not even statistically significant for life3, whereas it is highly significant at the 1% level for equity issuance with a t-statistic of -3.16 despite the aggressive controls for firm fixed effects.

Firms in the dynamic and high competition sample also experience massive increases in CAPX from 0.015 to 0.108 per unit of life2 when tobins Q increases. Given the high stakes, and the frequent occurrence of winner-takes-all outcomes in competitive and entrepreneurial markets, our findings for R&D, CAPX, and equity issuance in these markets are very intuitive.

Many other important results for the other subsamples are also economically large in magnitude. For example, dynamic firms in less competitive markets have the luxury of being more opportunistic regarding their innovative activities. Per unit of life1, these firms increase their acquisitions from essentially zero to 3.2% of assets and they also increase their R&D from 3.3% to 4.7% of assets when their Q increases. Both are also statistically significant. These same firms also become remarkably active when their products fall into decline. In particular, per unit of life4, when Q increases, they increase acquisitions from a negative predicted value of -4.3% of assets to a very substantial 6.7% of assets, and R&D from 1.1% to 5.5%. In contrast to dynamic firms in competitive markets, which rely on equity financing, these dynamic firms finance these activities using debt, which increases from essentially zero to 15.3% of assets when Q increases.

Although there are other economically important results in Table 10, we leave further exploration to the reader for parsimony. Yet we conclude with a final point. The last two columns report the Q-sensitivity in each subsample associated with the basic model used in the literature. In contrast to the results reported for the conditional model, the resulting Q-sensitivities are much smaller in magnitude and largely devoid of the rich economic conclusions we were able to draw when we put the Q-sensitivities into the context of the life cycle exposures. We also note that the basic model is unable to report any conclusions regarding the conditional intercepts noted above, and moreover, without the text based life cycle model, the four subsamples shown here also could not be identified. In conclusion, the life cycle model provides very strong results statistically, and they are backed by very large economic magnitudes and economic insights that can further extend our knowledge regarding how firms choose corporate policies.

7 Investment, Acquisitions, and Outcomes

7.1 Basic Q-investment Regressions

In the last section we examined the relation between product life cycles, Q and corporate policies over our entire sample period. We next investigate how these relations have changed over the previous 17 years.

We first examine the time series relationship between equity issuance and Tobins Q. In particular, we run annual regressions where equity issuance/assets is the dependent variable, and we consider two models for RHS variables at the firm level. The first is the basic model from the existing literature, where Tobins Q, size and age are the RHS variables. The table shows (not surprisingly given the literature) that Tobins Q is positive and highly significant in predicting equity issuance and that this relationship is stable over time. We note that these results differ from Lee, Shin and Stulz (2016) who examine equity issuance that is net of repurchases, whereas we examine pure equity issuance given the importance of capital raising for smaller and more innovative firms, which are central to our study of innovation and life cycles.

[**Insert Table 11 Here**]

We next consider the conditional Q model, which includes the life cycle states life1 to life4 (with life3 omitted due to collinearity with the intercept), and also the interaction between each life cycle variable and Tobins Q. The table echoes our earlier findings. We observe that life1 firms have very strong and reliably positive sensitivities to Tobins Q. Moreover, the sensitivity coefficients are roughly 3x as large as the Tobins Q sensitivity coefficients in the basic model. We also note a second main result in the paper that life3 exposures reduce the sensitivity of equity issuance to Tobins Q. This illustrates the hedging role of mature products. When included in a firm's portfolio with more innovative life1 products, the mature cashflows from life3 products can help to fund the research and development associated with life1 products, thus reducing the need to raise capital externally.

We next 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 12. 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 12 Here**]

We next examine if the conditional model of Tobins Q for CAPX/assets performs differently, as was the case for equity issuance. 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 12 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. Table 12 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 13 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 13. 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 in Table 13 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 14. 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 14 Here**]

Overall we conclude that the relation 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.

7.2 Explaining the Declining Explanatory Power of Q for CAPX

To better understand the relation between CAPX and Tobins Q, we consider the plots of adjusted R^2 over time for different model specifications and sample cuts. The top graph in Figure 4 plots R^2 from the basic model in the left panel of Table 12, regressing CAPX on Tobin's Q, with age and firm size as controls.

The blue line of the top graph illustrates, as shown in the left panel of Table 12, the explanatory power of the Q regression is generally low, and it peaks in 2003. We next break the sample into firms with above and below median dynamism, using annual breakpoints and two results emerge. First, Tobin's Q explains CAPX much better for firms with below median dynamism (grey line), which we refer to as static firms, than for firms with above median dynamism (orange line), which we term dynamic firms. The adjusted R^2 of the static subsample is approximately twice that of the dynmic subsample. Second, when we consider static and dynamic firms separately, there is no evidence that the explanatory power of Q is falling over time in either subsample. The declining trend in the total population thus arises from the aggregations of two distinct populations.

In the next two graphs we further break the sample into above median and below median TNIC total similarity competition subsamples, again using annual median breakpoints. Firms with high total similarity follow a pattern that is similar to the whole sample, albeit with significantly higher R^2 in each year. In contrast, there is no discernible pattern in the low total similarity subsample, and explanatory power is also much lower. Thus, we conclude that the CAPX-Q model has the most explanatory power for static firms operating in more competitive markets. The CAPX of dynamic firms is not overly sensitive to market signals across the spectrum of total similarity. These firms are following a more entrepreneurial agenda, and not responsive to short term market signals.

In Figure 5 we repeat the exercise of plotting the R^2 for key subsamples. However, this time we use the conditional CAPX-Q model in the middle panel of Table 12. This specification permits the life-cycle state of each firm to moderate the CAPX-Q relation.

[**Insert Figure 5 Here**]

The adjusted R^2 coefficients are higher and are also increasing through time across the board, indicating that firms' CAPX is sensitive to both life cycle states and market signals in all subsamples. The in increase in explanatory power is also much greater for dynamic firms. Thus, knowing the life-cycle stage of these firms, especially those facing higher competition, leads to increases in explanatory power.

In Figure 6 we investigate how much of the explanatory power of the conditional model is due to adding the life variables alone, versus adding both the life variables and their interactions with Q (the conditional Q model).

[**Insert Figure 6 Here**]

Overall, much of the explanatory power comes from the life variables. This is particularly true for dynamic firms in high total similarity regions of the TNIC network. The exception to this pattern occurs in the sample of static high competition firms, whose CAPX is particularly sensitive to the life state and Tobins Q cross terms. Overall, the use of life cycle variables is instrumental in explaining investment behavior and the conditional model shows no evidence of a decline in explanatory power over the sample period.

We control for firm age in all of our tests, and in unreported analysis, we also note that additional controls for age squared do not change our inferences. Because age is used as a life cycle variable in prior studies, it is important to further stress test whether a more rigorous transformation of firm age can replicate our results for the test-based life cycle. Because our text-based model is based on four groupings, we sort firms based on their age into quartiles in each year. We then consider the "most analogous" firm-age based life cycle, which defines life1 as firms in the youngest quartile, life2 and life3 as the second and third quartiles, and life4 as the oldest firm quartile. We then rerun the conditional Q model using the age-based life cycle and its interactions with Q.

[**Insert Figure 7 Here**]

Figure 7 compares the results of the age-based life cycle to the results for both the basic model and the text-based life cycle model. Both life cycles produce higher adjusted R^2 than the basic model. However, the age based life cycle's improvement is very small economically whereas the text-based life cycle offers much larger improvements in explanatory power. This test strongly reinforces the conclusion that firm age does not contain adequate information or dimensionality to richly model the product life cycle, where as the text-based approach offers significant advances.

7.3 International Competition and Expansion

We next examine if firms facing increased levels of international competition, or international growth options, experience changes in their life cycle status. Our goal is to explore whether these forces are at least partly responsible for changes in the specific life cycle stages and thus the increases in firm dynamism we reported earlier. Intuitively, international shocks of either sort are a form of market disruption, and life cycle theory would suggest that standard strategies that firms adopt in the life cycle are likely in need of revision to accommodate the disruption. It is further relevant to explore if such shocks differentially impact firms that are ex-ante in more innovative or mature states.

We measure International competition at the firm level as a dummy equal to one if a firm has at least one paragraph in its 10-K mentioning a word from { international, foreign} and also the word competition. International growth opportunities is a similar dummy equal to one if the firm has at least one paragraph mentioning a word from { international, foreign} and a word from { expand, expansion, growth, increase, increasing }.

In our regressions, we regress our ex post life cycle variables on ex ante values of international competition and international growth options as defined above. We first consider the firm level measures of both international RHS variables, and we then consider the average of both over distant TNIC industry peers. The use of distant peers is less endogenous from the perspective of an individual firm's policies. 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 identify distant peers as those that are in a firm's TNIC-2 industry but not in a firm's TNIC-3 industry. All RHS variables used in our regressions are ex ante measurable from year $t - 1$. All specifications include firm and year fixed effects and standard errors are clustered by firm.

[Insert Table 15 Here]

Table 15 displays the results. Panel A displays results for the international competition shock. We find that, regardless of whether measured at the firm level or as a broader shock to distant peers, international competition induces firms to down-weight their exposure to life3 and increase their exposure to life1. These results, particularly the increase in life1, is highly significant. Given our earlier definition of firm dynamism, these results directly imply that international competition induces firms to become more innovative and dynamic. This is consistent with re-tooling product offerings to be competitive on a more global stage.

We note that the underlying force behind international competition is globalization and the opening of borders. The entry of foreign competitors is one consequence, but not the only one. The other consequence is that the U.S. firms will have a new set of growth options to enter the foreign markets associated with the opening borders. Hence we examine international growth options. We first note, consistent with this intuition, that both international variables are roughly 65% correlated. Hence the opening of borders is a broader form of market disruption than competition alone.

Panel B of Table 15 displays the results for international growth opportunities. As expected, we again find a strong shift toward the most innovative life cycle stage, life1. The results are even stronger than those in Panel A. One additional difference is that firms down-weight cost cutting (life2) and also product discontinuation (life4) in order to increase their exposures to life1. This is consistent with growth options requiring a more intensive focus on product development. One reason could be that international consumers favor different product features than do domestic consumers. Also, the global market may demand higher quality product offerings to be competitive.

Overall these findings suggest that the shift toward the dynamic firm, in part, is potentially driven by forces related to globalization through the lens of international competition and growth opportunities.

8 Conclusion

Motivated by theories of product life cycles, for example Abernathy and Utterback (1978), we develop a four-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. Theory suggests that each life-cycle stage is associated with different mixes of tangible and intangible investments, and different financing choices. We build our life cycle model using text based analysis of firm 10-Ks. This approach allows us to obtain metrics for each firm annually, and examine firm progression through the life cycle, investment policies, and financing policies.

A main finding is that understanding the firm's exposure to product life cycle stages has a first order impact on understanding financing and investment policies. In recent years large firms in public markets have diversified their exposures to product life cycle stages, by becoming more entrepreneurial. This diversification groups cash-flow-negative entrepreneurial product investments alongside cash-flow-positive mature product lines, all within a single firm's boundaries. Once we control for firm-level composition changes and account for the life cycle, we provide a new explanation for the puzzle identified by Doidge et al (2018) that public funding does not robustly flow to high-Q firms. We find a normal relationship between Q and external capital financing when using our conditional life cycle model.

Simply conditioning the investment-Q model on the life cycle of the firm radically changes the inferences from the existing literature. For example, existing studies report that the Q model has been losing its explanatory power in recent years. Once we account for the life cycle, we observe strong increases in the explanatory power of the investment-Q model. These changes are strongly related to a secular trend toward firms shifting their life cycle strategies toward more innovative dispositions. Furthermore, competition interacts with exposures to the product life cycle. Broadly, firms that are more dynamic and that operate in competitive markets are most sensitive to Q, both on the financing and investment side. In contrast, dynamic firms facing less competition become highly sensitive to Q when they are in the latest stage of the cycle, product decline. This suggests that dynamic firms in less competitive markets can be more opportunistic when they face increasing obsolescence, in some cases allowing them to return to youthful states through newly initiated product development.

We also show that market shocks, such as global competition, the financial crisis, and the technology bust, lead to changes in firm life cycle stages across the market. Following the technology bust of 2000 to 2002 and the financial crisis, firms in the more innovative life cycle stages transition 1-2 stages toward less active stages. Many firms with an ex ante focus on product innovation transition to maturity, and some transition to delisting. Firms focused on the process innovation also transition to maturity and decline. Since life cycle exposures are sticky, these results suggest that there are potentially important long term consequences of major shocks, as they can impair innovative product strategies for prolonged periods. Regarding globalization, we find using textual mentions of international competition and growth that broad industry-wide shifts in globalization are likely a factor in explaining why large U.S. firms are becoming more dynamic.

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. We believe that examining corporate finance policies through the lens of the product life cycle can yield many novel results in finance and economics.

References

Abernathy, William J., and James M. Utterback, 1978, Patterns of industrial innovation, *Technology Review* 80, 41–47.

Aghion, P., N. Bloom, R. Blundell, R. Griffith, P. Howitt. (2005). Competition and Innovation: An Inverted-U Relationship. *Quarterly Journal of Economics*, 120(2), 701-728.

Arikan, Asli M., and Rene M. Stulz, 2016, Corporate Acquisitions, Diversification, and the Firm's Lifecycle,*Journal of Finance*

Autor, D, D Dorn, G H Hanson, G Pisano and P Shu (2016), Foreign Competition and Domestic Innovation: Evidence from U.S. Patents. CEPR Discussion Paper No. 11664.

Bertrand, M., and Schoar, A., 2003. Managing with Style: The effect of managers on firm policies. Quarterly Journal of Economics, 118, 1169-1208

Bloom, N (2017) Corporation in the Age of Inequality, *Harvard Business Review*

Bloom, N., and Van Reenen, J., 2007. Measuring and explaining management practices across 33 firms and countries. *Quarterly Journal of Economics* 122:4, 1351-1408.

Bloom, N., and Van Reenen, J., 2010. "Why do management practices differ across firms and countries?" *Journal of Economic Perspectives* 24(1), 203-224.

Bloom, N., Eifert, B., Mahajan, A., McKenzie, D., and Roberts, J. 2013. "Does Management Matter? Evidence from India," *Quarterly Journal of Economics*, 128(1), 1-51.

Bloom, N., Draca, M., and Van Reenen, J. (2016). Trade induced technical change? The impact of Chinese imports on innovation, IT and productivity. *The Review of Economic Studies*, 83(1), 87-117.

Chen, H., and S. Chen, 2012. Investment-cash flow sensitivity cannot be a good measure of financial constraints: Evidence from the time series. *Journal of Financial Economics*, 103(2), 393-410.

DeAngelo, Harry, Linda DeAngelo and Rene Stulz, 2010. Seasoned Equity Offerings, Market Timing, and the Corporate Lifecycle. *Journal of Financial Economics*, 95, 275-295.

DeAngelo, Harry, Linda DeAngelo and Toni Whited, 2011. Capital structure dynamics and transitory debt. *Journal of Financial Economics*, 99, 235-261.

Doidge, C., Kahle, K.M., Karolyi,G. A., and Stulz,R.M., 2018. Eclipse of the Public Corporation or Eclipse of the Public Markets? National Bureau of Economic Research Working Paper Series No. 24265, http://www.nber.org/papers/w24265.

Erickson, Timothy, and Toni M. Whited, 2000, Measurement error and the relationship between investment and q, *Journal of Political Economy* 108, 1027-1057.

Fresard, Laurent, Gerard Hoberg, and Gordon Phillips, 2017, Vertical Acquisitions, Integration and the Boundaries of the Firm, Working paper.

Frick, W. (2016) Corporate Inequality Is the Defining Fact of Business Today, *Harvard Business Review.*

Guadalupe, M., and Wulf, J. (2010). The flattening firm and product market competition: The effect of trade liberalization on corporate hierarchies. *American Economic Journal: Applied Economics*, 2(4), 105-127

Grullon, G., Y. Larkin, and R. Michaely (2016). Are us industries becoming more concentrated. Technical report, Working paper

Gutierrez, G., and Philippon, T. (2016). Investment-Less Growth: An Empirical Investigation, NBER Working Paper No: 22897 http://www.nber.org/papers/w22897

Gutierrez, G., and Philippon, T. (2017). Declining Competition and Investment in the US, working paper.

Hassett, Kevin. A., and R. Glenn Hubbard, 1997, Tax policy and investment, in Fiscal Policy: Lessons from the Literature, A. Auerbach, ed. (Cambridge, MA: MIT Press).

Hayashi, Fumio, 1982, Tobin's marginal q and average q: A neoclassical interpretation, *Econometrica* 50, 213224.

Hennessy, C., and Levy, A., and T. Whited, 2007. Testing Q Theory with Financing Frictions. *Journal of Financial Economics*, 83 (, 691-717.

Hoberg, Gerard, and Vojislav Maksimovic, 2015, Redefining Financial Constraints: a Text-Based Analysis, *Review of Financial Studies* 28, 1312-1352.

Hoberg, Gerard, and Katie Moon, 2017, Offshore Activities and Financial vs Operational Hedging, *Journal of Financial Economics, forthcoming.*

Hoberg, Gerard, and Gordon Phillips, 2010, Product market synergies in mergers and acquisitions: A text based analysis, *Review of Financial Studies* 23, 3773–3811.

Hoberg, Gerard, and Gordon Phillips, 2016, Text-Based Network Industries and Endogenous Product Differentiation, *Journal of Political Economy*, 124, 1423-1465.

Hoberg, Gerard, Gordon Phillips, and Nagpurnanand Prabhala, 2014, Product Market Threats, Payouts, and Financial Flexibility, *Journal of Finance*, 69, 293-324..

Klepper, Steven, 1996, Entry, exit, growth, and innovation over the product life cycle, *American Economic Review* 86, 562–583.

Klepper, S., and Thompson, P. (2006). Submarkets and the evolution of market structure. *The RAND Journal of Economics, 37(4), 861-886.*

Lee D., Shin H., and R.M. Stulz, 2016, Why Does Capital No Longer Flow More to the Industries with the Best Growth Opportunities? NBER Working Paper No. 22924.

Loderer, C., Stulz, R., and U. Waelchli. (2016). Firm Rigidities and the Decline in Growth Opportunities. *Management Science*, 1-20.

Maksimovic, V. 1988. Capital structure in repeated oligopolies, *The RAND Journal of Economics*, 389-407

Maksimovic, V., and G Phillips, 2008, The industry life cycle, acquisitions and investment: Does firm organization matter? *Journal of Finance.*

Magyari, I. (2017). Firm Reorganization, Chinese Imports, and US Manufacturing Employment, Columbia Department of Economics.

Malmendier, U., Tate, G., and Yan, J. 2011. Overconfidence and Early-life Experiences: The Effect of Managerial Traits on Corporate Financial Policies, Journal of Finance, 66, 1687-1733.

Nekarda, C. J., and Ramey, V. A. (2013). The cyclical behavior of the price-cost markup (No. w19099). National Bureau of Economic Research.

Peters R.H, and L.A. Taylor. 2017.Intangible capital and the investment-q relation, *Journal of Financial Economics* 123 (2), 251-272

Philippon, Thomas, 2009, The bond market's q, *Quarterly Journal of Economics* 124, 10111056.

Rajan, R. G., and Wulf, J. (2006). The flattening firm: Evidence from panel data on the changing nature of corporate hierarchies. *Review of Economics and Statistics*, 88(4), 759-773.

Whited T., and G. Wu, 2006, Financial Constraints Risk, *Review of Financial Studies* 19, 531-559.

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
			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 (Panel A) and autoregressive coefficients (Panel B) 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). The autoregressive coefficients in Panel B are equal to the OLS coefficient obtained when regressing each variable on its lagged value. 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
Panel A: 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

Row Statisic	Life1	Life2	Life3	Life4
Panel B: Persistence Statistics				
AR(1) Coefficient	0.861	0.874	0.812	0.764

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 TNIC 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 TNIC 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: 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 7: Issuance Panel Data Regressions

The table reports selected results from firm-year panel data investment-Q regressions from 1998 to 2015. The dependent variable is ex post equity issuance/assets (Panels A, B) or debt issuance/assets (Panels C, D) in year t. All RHS variables are ex ante measurable and are observable in year $t-1$ and are either value-weighted using year $t-1$ assets (Panels A, C) or are equal weighted (Panels B and D). In all models, the dependent variable is regressed on ex-ante life cycle variables, Tobins Q, and size plus age controls. All ratio variables are winsorized at the 1/99% level. The last two columns indicate the adjusted R^2 and the number of observations. All regressions include firm and year fixed effects. t-statistics (clustered by firm) are reported in parentheses.

	Basic Model			Conditional Model										
Row	Tobins Q	Log Assets	Log Age	Life1	Life2	Life4	TobQ x Life1	TobQ x Life2	TobQ x Life3	TobQ x Life4	Log Assets	Log Age	Adj R^2	# Obs
				Panel A: Equity Issuance (Value Weighted)										
(1)	0.008	–0.009	–0.014	–0.008	0.003	0.007	0.017	0.008	0.001	–0.010	–0.009	–0.014	0.230	76,135
	(8.000)	(–6.440)	(–4.460)	(–0.840)	(0.270)	(0.700)	(3.770)	(2.340)	(0.330)	(–1.010)	(–6.400)	(–4.240)		
(2)	0.008	–0.015	–0.026	–0.094	–0.069	–0.059	0.030	0.010	–0.034	0.006	–0.016	–0.026	0.180	38,079
	(4.770)	(–4.430)	(–4.990)	(–4.280)	(–3.870)	(–2.510)	(4.930)	(2.560)	(–3.300)	(0.480)	(–4.470)	(–5.310)		
(3)	0.009	–0.005	–0.011	0.005	0.007	0.012	0.011	0.017	0.005	–0.016	–0.005	–0.011	0.330	38,056
	(7.780)	(–3.880)	(–3.750)	(0.380)	(0.430)	(1.000)	(1.560)	(1.600)	(0.930)	(–1.130)	(–3.870)	(–3.600)		
				Panel B: Equity Issuance (Equal Weighted)										
(4)	0.038	–0.083	–0.019	–0.116	–0.046	–0.218	0.089	0.015	–0.018	0.107	–0.084	–0.019	0.382	76,135
	(15.490)	(–23.750)	(–2.990)	(–4.020)	(–2.300)	(–4.290)	(8.900)	(2.180)	(–1.550)	(2.670)	(–24.120)	(–3.050)		
(5)	0.043	–0.107	–0.023	–0.239	–0.122	–0.321	0.106	0.010	–0.050	0.114	–0.108	–0.023	0.387	38,079
	(11.640)	(–18.810)	(–1.910)	(–3.440)	(–2.280)	(–3.820)	(7.090)	(1.290)	(–1.680)	(2.370)	(–19.310)	(–1.920)		
(6)	0.031	–0.059	–0.018	–0.039	–0.044	–0.036	0.063	0.041	–0.002	0.015	–0.060	–0.017	0.433	38,056
	(8.570)	(–12.500)	(–2.360)	(–0.920)	(–1.180)	(–0.560)	(3.070)	(2.100)	(–0.080)	(0.270)	(–12.540)	(–2.210)		
				Panel C: Debt Issuance (Value Weighted)										
(7)	0.010	–0.020	–0.006	0.072	–0.087	–0.058	–0.013	0.050	–0.001	0.027	–0.020	–0.010	0.525	76,135
	(3.350)	(–2.780)	(–0.560)	(1.810)	(–2.830)	(–1.080)	(–1.340)	(4.940)	(–0.110)	(0.760)	(–2.890)	(–0.910)		
(8)	0.010	–0.039	0.004	–0.057	–0.181	–0.256	–0.003	0.061	–0.066	0.102	–0.036	–0.001	0.525	38,079
	(2.310)	(–2.050)	(0.190)	(–0.640)	(–2.300)	(–2.170)	(–0.250)	(4.740)	(–2.090)	(2.480)	(–1.940)	(–0.040)		
(9)	0.009	–0.019	–0.014	0.115	–0.067	0.043	–0.017	0.018	0.025	–0.041	–0.020	–0.018	0.551	38,056
	(2.090)	(–2.770)	(–0.960)	(2.000)	(–1.560)	(0.560)	(–0.680)	(0.740)	(0.890)	(–0.640)	(–2.960)	(–1.320)		
				Panel D: Debt Issuance (Equal Weighted)										
(10)	0.008	–0.049	0.010	–0.010	–0.003	–0.173	0.001	0.017	0.005	0.027	–0.050	0.011	0.385	76,135
	(7.260)	(–12.520)	(1.070)	(–0.390)	(–0.150)	(–4.830)	(0.290)	(3.660)	(0.860)	(1.540)	(–12.700)	(1.200)		
(11)	0.008	–0.049	0.012	–0.084	–0.076	–0.273	0.007	0.015	–0.010	0.041	–0.050	0.013	0.389	38,079
	(5.480)	(–9.500)	(0.780)	(–1.670)	(–1.620)	(–4.440)	(1.150)	(2.780)	(–0.680)	(1.770)	(–9.690)	(0.910)		
(12)	0.008	–0.056	0.011	0.017	–0.019	–0.092	–0.007	0.040	0.004	0.007	–0.056	0.012	0.425	38,056
	(4.440)	(–9.000)	(0.860)	(0.430)	(–0.550)	(–1.420)	(–0.700)	(3.170)	(0.410)	(0.210)	(–8.980)	(0.940)		

Table 8: Investment Panel Data Regressions

The table reports selected results from firm-year panel data investment-Q regressions from 1998 to 2015. The dependent variable is ex post R&D/assets (Panels A, B), CAPX/Assets (Panels C and D) or dollars spent on acquisitions/assets (Panels E, F) in year t. All RHS variables are ex ante measurable and are observable in year $t-1$ and are either value-weighted using year $t-1$ assets (Panels A, C, and E) or are equal weighted (Panels B, D, and F). In all models, the dependent variable is regressed on ex-ante life cycle variables, Tobins Q, and size plus age controls. All ratio variables are winsorized at the 1/99% level. The last two columns indicate the adjusted R^2 and the number of observations. All regressions include firm and year fixed effects. t-statistics (clustered by firm) are reported in parentheses.

	Basic Model			Conditional Model										
Row	Tobins Q	Log Assets	Log Age	Life1	Life2	Life4	TobQ x Life1	TobQ x Life2	TobQ x Life3	TobQ x Life4	Log Assets	Log Age	Adj R^2	# Obs
				Panel A: R&D/Assets (Value Weighted)										
(1)	0.005	–0.005	0.001	–0.012	0.002	–0.030	0.015	–0.002	–0.002	0.032	–0.005	0.001	0.863	76,135
	(4.700)	(–3.960)	(0.840)	(–2.760)	(0.520)	(–2.730)	(5.030)	(–1.300)	(–0.670)	(2.250)	(–4.280)	(1.000)		
				Panel B: R&D/Assets (Equal Weighted)										
(2)	0.007	–0.025	0.006	–0.023	–0.010	–0.045	0.025	–0.001	–0.010	0.012	–0.025	0.007	0.828	76,135
	(14.830)	(–19.750)	(2.870)	(–3.480)	(–2.240)	(–4.320)	(11.650)	(–1.230)	(–4.120)	(1.450)	(–20.360)	(3.190)		
				Panel C: CAPX/Assets Issuance (Value Weighted)										
(3)	0.009	–0.005	–0.005	0.017	–0.027	–0.009	–0.005	0.032	0.006	0.003	–0.005	–0.007	0.780	76,135
	(7.370)	(–3.830)	(–1.630)	(2.270)	(–3.690)	(–0.700)	(–1.610)	(6.800)	(1.410)	(0.330)	(–3.800)	(–2.030)		
				Panel D: CAPX/Assets Issuance (Equal Weighted)										
(4)	0.007	–0.011	–0.011	0.033	–0.019	–0.036	–0.002	0.018	0.007	0.011	–0.011	–0.011	0.618	76,135
	(22.110)	(–14.340)	(–5.510)	(6.100)	(–2.770)	(–4.530)	(–1.240)	(5.930)	(3.610)	(1.910)	(–14.280)	(–5.540)		
				Panel E: Acquisitions/Assets (Value Weighted)										
(5)	0.004	–0.013	–0.001	0.015	–0.030	–0.046	–0.008	0.025	–0.002	0.019	–0.013	–0.002	0.124	74,891
	(2.850)	(–5.830)	(–0.240)	(1.780)	(–4.030)	(–1.730)	(–1.600)	(5.720)	(–0.370)	(0.620)	(–5.870)	(–0.630)		
				Panel F: Acquisitions/Assets (Equal Weighted)										
(6)	0.004	–0.018	–0.005	0.019	–0.030	–0.082	–0.009	0.010	0.012	0.022	–0.019	–0.005	0.153	74,891
	(8.700)	(–12.730)	(–1.650)	(2.210)	(–4.100)	(–6.010)	(–5.210)	(4.540)	(5.600)	(2.540)	(–13.110)	(–1.720)		

Table 9: Issuance and Investment (Dynamism and Competition Subsamples)

The table reports results from firm-year panel data issuance-Q and investment-Q regressions from 1998 to 2015. The dependent variable is ex post equity issuance/assets (Panel A), debt issuance/assets (Panel B, R&D/assets (Panel C), CAPX/Assets (Panel D) or dollars spent on acquisitions/assets (Panel E) in year t. To conserve space, each row reports the key results associated with four separate regressions: one for each of the four subsamples formed by sorting firms into above and below median values of ex ante year $t-1$ dynamism and competition. Competition is measured using TNIC total similarity (see Hoberg and Phillips 2016). The four subsamples for each regression are indicated by the header rows above each column. All RHS variables are ex ante measurable and are observable in year $t-1$ and all regressions are value-weighted using year $t-1$ assets. In all models, the dependent variable is regressed on ex-ante life cycle variables, Tobins Q, and size plus age controls. All ratio variables are winsorized at the 1/99% level. All regressions include firm and year fixed effects. t-statistics (clustered by firm) are reported in parentheses.

	Dynamic and Competitive				Dynamic and Low Competition				Static and Competitive				Static and Low Competition			
Row	TobQ x Life1	TobQ x Life2	TobQ x Life3	TobQ x Life4	TobQ x Life1	TobQ x Life2	TobQ x Life3	TobQ x Life4	TobQ x Life1	TobQ x Life2	TobQ x Life3	TobQ x Life4	TobQ x Life1	TobQ x Life2	TobQ x Life3	TobQ x Life4
								Panel A: Equity Issuance/Assets (Value Weighted)								
(1)	0.039	0.018	–0.052	0.004	0.019	0.004	–0.013	0.012	0.012	0.016	0.006	–0.019	0.008	0.024	–0.007	0.003
	(4.60)	(3.19)	(–3.16)	(0.20)	(1.84)	(0.62)	(–1.21)	(0.67)	(1.24)	(1.32)	(0.71)	(–0.87)	(0.72)	(1.29)	(–0.73)	(0.09)
								Panel B: Debt Issuance/Assets (Value Weighted)								
(2)	–0.004	0.094	–0.092	0.117	0.018	0.022	–0.067	0.135	0.002	–0.021	0.024	0.011	–0.021	0.042	–0.002	0.027
	(–0.22)	(4.76)	(–2.62)	(0.89)	(0.75)	(1.18)	(–1.20)	(4.43)	(0.04)	(–0.36)	(0.49)	(0.13)	(–0.73)	(1.63)	(–0.07)	(0.33)
								Panel C: R&D/Assets Issuance (Value Weighted)								
(3)	0.020	0.001	–0.011	0.011	0.012	–0.003	–0.007	0.044	0.011	0.000	0.000	0.015	0.008	–0.001	–0.002	0.033
	(3.72)	(0.32)	(–0.82)	(0.60)	(2.90)	(–1.23)	(–1.48)	(2.40)	(2.55)	(0.07)	(0.07)	(1.17)	(1.55)	(–0.38)	(–0.51)	(1.85)
								Panel D: CAPX/Assets Issuance (Value Weighted)								
(4)	–0.007	0.061	–0.033	0.044	0.007	0.014	0.008	0.016	–0.012	0.024	0.017	–0.012	–0.004	0.015	0.017	–0.019
	(–1.13)	(5.37)	(–2.78)	(1.36)	(0.94)	(1.71)	(0.50)	(1.97)	(–1.69)	(1.75)	(1.24)	(–0.64)	(–0.43)	(1.55)	(1.97)	(–0.82)
								Panel E: Acquisitions/Assets (Value Weighted)								
(5)	0.000	0.031	–0.024	–0.040	0.029	–0.002	–0.017	0.119	–0.023	0.023	0.014	0.020	–0.041	0.039	0.012	0.052
	(–0.02)	(3.59)	(–0.96)	(–1.23)	(2.25)	(–0.31)	(–0.70)	(2.41)	(–3.41)	(2.36)	(1.49)	(0.85)	(–2.40)	(2.64)	(0.64)	(1.23)

Table 10: Economic Magnitudes

The table reports the economic magnitude of our life cycle variables and of sensitivity to Tobins Q on issuance and investment variables. The economic magnitude variables are computed using the full sample models in Tables 7 8, and the analogous subsample models in Table 9 (see table for subsample descriptions). In all cases, we compute predicted values for hypothetical firms by first considering the average values of the dependent variables as representative of expected values for firms having all RHS variable characteristics set to their average values within each sample. We then consider perturbing only the life cycle variables and the tobin's Q to hypothetical alternative values in order to examine the differences in the predicted values of each dependent variable. In particular, within each sample, we consider perturbations of Tobin's Q to the 25th and 75th percentile within each sample. The average value of the dependent variable, and the 25th, 50th, and 75th percentile values of Tobin's Q are displayed in the first four columns after the first two columns (which identify the dependent variable and the sample. The next 8 columns show the predicted values of the given dependent variable for 8 hypothetical firms. These are (in order): a firm with a 100% loading on the life1 state and a Q in the 25th %ile, and a firm with a 100% loading on the life1 state and a Q in the 75th %ile. The next six columns are based on analogous hypothetical firms for the life cycle states life2, life3, and life4. The last two columns are based on the basic Tobins Q model, where the RHS variables only include Tobins Q, size, and age. Here we have greatly reduced degrees of freedom to model hypothetical firms, and hence we only consider two cases: a firm with a Q in the 25th %ile, and a firm with a Q in the 75th %ile. As noted earlier, all other characteristics modeled here are set to the subsample averages. We consider these tests of economic significance for equity issuance/assets, debt issuance/assets, CAPX/assets, R&D/assets, and dollar acquisitions from Compustat/assets.

							Life Cycle Conditional Model									
				Tobins Q Percentiles			Life1 Firm		Life2 Firm		Life3 Firm		Life4 Firm		Basic Model	
Row	Dependent Variable	Subsample	Mean Dep. Var	25th %ile Q	Median Q	75th %ile Q	Pred Low Q D Var	Pred Hi Q D Var	Pred Low Q D Var	Pred Hi Q D Var	Pred Low Q D Var	Pred Hi Q D Var	Pred Low Q D Var	Pred Hi Q D Var	Pred Low Q D Var	Pred Hi Q D Var
1	Equity Iss	Full Sample	0.059	0.676	1.077	1.846	0.051	0.071	0.055	0.067	0.050	0.048	0.048	0.031	0.051	0.061
2	Equity Iss	Dyn & Hi Comp	0.109	0.824	1.336	2.506	0.085	0.149	0.088	0.123	0.125	0.036	0.093	0.105	0.095	0.113
3	Equity Iss	Static & Hi Comp	0.040	0.296	0.686	1.375	0.036	0.041	0.036	0.052	0.025	0.036	0.030	0.009	0.033	0.041
4	Equity Iss	Dyn & Lo Comp	0.048	0.792	1.117	1.785	0.034	0.046	0.043	0.051	0.068	0.049	0.039	0.051	0.046	0.049
5	Equity Iss	Static & Lo Comp	0.040	0.803	1.152	1.835	0.039	0.039	0.030	0.058	0.035	0.030	0.035	0.034	0.035	0.042
6	Debt Iss	Full Sample	0.121	0.676	1.077	1.846	0.174	0.162	0.065	0.121	0.104	0.099	0.073	0.100	0.112	0.123
7	Debt Iss	Dyn & Comp	0.120	0.824	1.336	2.506	0.122	0.122	0.064	0.215	0.100	-0.075	0.015	0.173	0.111	0.123
8	Debt Iss	Static & Comp	0.093	0.296	0.686	1.375	0.193	0.207	0.011	0.011	0.080	0.088	0.136	0.148	0.084	0.095
9	Debt Iss	Dyn & Lo Comp	0.133	0.792	1.117	1.785	0.104	0.142	0.118	0.130	0.207	0.133	0.009	0.153	0.127	0.135
10	Debt Iss	Static & Lo Comp	0.138	0.803	1.152	1.835	0.114	0.091	0.156	0.202	0.128	0.132	-0.027	-0.019	0.131	0.140
11	CAPX/Assets	Full Sample	0.051	0.676	1.077	1.846	0.051	0.048	0.030	0.066	0.039	0.044	0.027	0.032	0.042	0.053
12	CAPX/Assets	Dyn & Comp	0.071	0.824	1.336	2.506	0.077	0.072	0.015	0.108	0.061	0.008	0.043	0.116	0.058	0.074
13	CAPX/Assets	Static & Comp	0.031	0.296	0.686	1.375	0.028	0.020	0.011	0.035	0.024	0.039	0.023	0.011	0.024	0.032
14	CAPX/Assets	Dyn & Lo Comp	0.055	0.792	1.117	1.785	0.070	0.078	0.042	0.058	0.031	0.031	0.025	0.041	0.046	0.056
15	CAPX/Assets	Static & Lo Comp	0.048	0.803	1.152	1.835	0.050	0.041	0.052	0.068	0.027	0.048	0.001	-0.021	0.041	0.050
16	R&D/Assets	Full Sample	0.047	0.676	1.077	1.846	0.043	0.062	0.045	0.042	0.044	0.040	0.036	0.077	0.042	0.048
17	R&D/Assets	Dyn & Comp	0.101	0.824	1.336	2.506	0.085	0.124	0.097	0.097	0.096	0.082	0.091	0.118	0.089	0.104
18	R&D/Assets	Static & Comp	0.032	0.296	0.686	1.375	0.027	0.035	0.030	0.032	0.029	0.032	0.028	0.034	0.028	0.033
19	R&D/Assets	Dyn & Lo Comp	0.033	0.792	1.117	1.785	0.033	0.047	0.030	0.028	0.035	0.021	0.011	0.055	0.030	0.033
20	R&D/Assets	Static & Lo Comp	0.024	0.803	1.152	1.835	0.026	0.029	0.027	0.024	0.019	0.020	0.021	0.057	0.024	0.025
21	$Acq/Assets	Full Sample	0.031	0.676	1.077	1.846	0.037	0.026	0.016	0.045	0.027	0.024	-0.004	0.010	0.029	0.031
22	$Acq/Assets	Dyn & Comp	0.024	0.824	1.336	2.506	0.033	0.029	0.005	0.056	0.027	-0.011	-0.028	-0.122	0.021	0.025
23	$Acq/Assets	Static & Comp	0.023	0.296	0.686	1.375	0.023	-0.000	0.005	0.029	0.021	0.033	0.016	0.031	0.023	0.023
24	$Acq/Assets	Dyn & Lo Comp	0.032	0.792	1.117	1.785	-0.001	0.032	0.022	0.014	0.068	0.069	-0.043	0.067	0.021	0.034
25	$Acq/Assets	Static & Lo Comp	0.045	0.803	1.152	1.835	0.071	0.032	0.043	0.085	0.021	0.032	-0.072	-0.039	0.040	0.046

Table 11: Equity Issuance-Q Regressions

The table reports selected results from annual OLS equity issuance-Q regressions from 1997 to 2015. Regressions are run separately in each year and each regression is thus purely cross sectional, and one observation is one firm. The dependent variable in all models is ex post equity issuance/assets in year t. All RHS variables are ex ante and are observable in year $t-1$. In all, the results are based on four models. The first block of four columns reports results for a basic investment-Q regression where equity issuance/assets is regressed on ex-ante Tobins Q plus log age and log size controls. The second block of 9 columns is the conditional model, where equity issuance/assets 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	2.397	-0.007	-0.013	0.161	-0.023	-0.009	N/A	-0.075	5.389	0.509	-0.395	7.397	0.183	0.184	0.203
	(24.1)	(-3.14)	(-14.5)		(-1.08)	(-0.49)		(-1.79)	(12.9)	(1.29)	(-0.73)	(3.59)			
(2) 1999	2.750	-0.013	-0.014	0.223	0.049	0.022	N/A	-0.028	4.092	0.340	2.625	8.277	0.242	0.181	0.229
	(31.7)	(-5.25)	(-14.4)		(2.34)	(1.25)		(-0.59)	(11.2)	(1.04)	(6.32)	(3.59)			
(3) 2000	1.446	-0.007	-0.025	0.227	0.215	0.015	N/A	-0.053	2.502	0.560	-0.648	10.43	0.282	0.390	0.441
	(28.9)	(-2.36)	(-20.2)		(8.98)	(0.75)		(-1.15)	(9.71)	(2.68)	(-2.15)	(9.43)			
(4) 2001	1.472	-0.008	-0.012	0.153	0.042	-0.009	N/A	0.000	3.616	0.549	-1.066	-1.141	0.188	0.230	0.321
	(24.0)	(-3.48)	(-14.0)		(2.35)	(-0.57)		(0.01)	(14.3)	(2.11)	(-3.02)	(-0.80)			
(5) 2002	2.081	-0.007	-0.008	0.185	-0.070	-0.013	N/A	-0.058	5.543	0.594	-1.568	6.075	0.223	0.223	0.276
	(27.5)	(-3.52)	(-11.5)		(-4.22)	(-0.94)		(-1.88)	(17.6)	(2.20)	(-3.83)	(3.74)			
(6) 2003	2.695	-0.011	-0.011	0.197	-0.003	0.006	N/A	-0.069	8.441	0.671	-2.730	7.382	0.267	0.143	0.261
	(24.8)	(-4.87)	(-14.2)		(-0.16)	(0.40)		(-2.13)	(17.8)	(2.03)	(-5.03)	(3.74)			
(7) 2004	2.146	-0.010	-0.013	0.212	0.002	0.026	N/A	-0.033	6.566	0.154	-1.068	3.501	0.268	0.299	0.392
	(23.4)	(-3.87)	(-14.3)		(0.09)	(1.50)		(-0.92)	(16.0)	(0.60)	(-2.25)	(1.89)			
(8) 2005	2.187	-0.010	-0.009	0.187	-0.100	0.003	N/A	-0.134	9.116	-0.381	-3.369	8.738	0.275	0.194	0.223
	(22.6)	(-4.42)	(-9.50)		(-4.49)	(0.17)		(-3.78)	(21.0)	(-1.37)	(-6.92)	(4.90)			
(9) 2006	2.287	-0.013	-0.009	0.172	-0.057	0.003	N/A	0.035	9.438	-0.130	-2.931	-3.695	0.248	0.158	0.236
	(20.3)	(-5.39)	(-10.2)		(-2.35)	(0.14)		(0.87)	(18.4)	(-0.36)	(-5.16)	(-1.68)			
(10) 2007	1.408	-0.014	-0.009	0.128	0.026	0.050	N/A	0.018	6.003	-0.165	-2.062	-2.044	0.203	0.119	0.194
	(14.9)	(-6.19)	(-10.2)		(1.19)	(3.06)		(0.49)	(14.5)	(-0.66)	(-4.46)	(-1.01)			
(11) 2008	1.060	-0.006	-0.005	0.086	-0.020	0.010	N/A	-0.027	4.497	0.172	-2.124	2.157	0.130	0.195	0.226
	(14.0)	(-3.57)	(-6.97)		(-1.14)	(0.74)		(-0.91)	(12.5)	(0.82)	(-5.23)	(1.29)			
(12) 2009	1.853	-0.015	-0.009	0.112	-0.009	0.032	N/A	-0.055	8.695	-0.198	-4.557	7.599	0.184	0.104	0.187
	(13.4)	(-6.80)	(-10.5)		(-0.40)	(2.02)		(-1.47)	(14.5)	(-0.49)	(-6.49)	(2.56)			
(13) 2010	3.080	-0.012	-0.008	0.219	-0.103	-0.001	N/A	-0.100	11.51	0.486	-5.137	10.73	0.326	0.193	0.323
	(25.2)	(-5.01)	(-8.71)		(-4.76)	(-0.04)		(-2.69)	(23.1)	(1.44)	(-9.00)	(4.45)			
(14) 2011	1.994	-0.012	-0.009	0.167	-0.018	0.012	N/A	-0.107	6.845	-0.031	-2.833	10.83	0.247	0.191	0.238
	(18.8)	(-4.91)	(-9.68)		(-0.84)	(0.75)		(-2.64)	(15.7)	(-0.11)	(-5.83)	(4.50)			
(15) 2012	1.918	-0.017	-0.010	0.148	0.093	0.062	N/A	-0.066	6.964	-0.409	-2.609	10.89	0.246	0.173	0.271
	(15.3)	(-6.56)	(-10.0)		(3.98)	(3.66)		(-1.40)	(13.0)	(-1.22)	(-4.33)	(3.39)			
(16) 2013	2.392	-0.021	-0.012	0.205	0.033	0.071	N/A	0.017	9.608	-1.193	-1.935	0.911	0.308	0.198	0.283
	(19.0)	(-6.88)	(-10.8)		(1.28)	(3.78)		(0.39)	(17.7)	(-3.56)	(-3.16)	(0.43)			
(17) 2014	2.083	-0.018	-0.016	0.196	0.047	0.070	N/A	0.074	8.665	-1.768	-2.065	-5.018	0.296	0.200	0.298
	(16.0)	(-5.64)	(-13.3)		(1.58)	(3.15)		(1.40)	(15.9)	(-4.14)	(-3.14)	(-1.90)			
(18) 2015	2.551	-0.027	-0.014	0.223	0.088	0.106	N/A	0.067	7.458	-1.878	0.603	-0.904	0.300	0.179	0.294
	(18.8)	(-8.37)	(-11.3)		(2.88)	(4.52)		(1.07)	(14.0)	(-3.94)	(0.87)	(-0.25)			

Table 12: 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. All RHS variables are ex ante and are observable in year $t-1$. In all, the results below are based on four models. The first block of four columns is a basic investment-Q regression where CAPX/assets is regressed on ex-ante Tobins Q plus basic controls. The second block of 9 columns is the conditional model, where CAPX/assets 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 13: 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. All RHS variables are ex ante and are observable in year $t-1$. 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/assets is regressed on ex-ante Tobins Q plus basic controls. The second block of 9 columns is the conditional model, where R&D/assets 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 14: 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. All RHS variables are ex ante and are observable in year $t-1$. 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 the acquisition dummy 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 15: International Competition and International Growth Opportunity 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 variable as noted in the first column. Key is the shock variable, which is either the international competition textual measure (Panel A) or the international growth opportunities textual measure (Panel B). The international growth measure and the international competition measures are both first computed at the firm level (results displayed in odd number rows) and then averaged over distant TNIC industry peers as using distant peers is less endogenous from the perspective of an individual firm's policies. Distant peers are those that are in a firm's TNIC-2 industry but not in a firm's TNIC-3 industry. International competition is dummy equal to one if a firm has at least one paragraph mentioning a word from { international, foreign} and also the word competition. International growth opportunities is a similar dummy equal to one if the firm has at least one paragraph mentioning a word from { international, foreign} and a word from { expand, expansion, growth, increase, increasing }. All RHS variables are ex ante measurable in year $t-1$. All specifications include firm and year fixed effects. Standard errors are clustered by firm. t-statistics are in parentheses.

Row	Dependent Variable	Own-Firm Shock	Distant Peer Shock	Log Age	Log Assets	Tobins Q	10-K Size	Obs/ R^2
			Panel A: Text-Based International Competition Shock					
(1)	life1	0.007		-0.009	0.007	0.006	-0.003	77,170
		(5.81)		(-3.64)	(3.55)	(11.2)	(-8.01)	0.812
(2)	life1		0.030	-0.010	0.007	0.006	-0.003	76,058
			(5.69)	(-4.02)	(3.51)	(11.0)	(-7.92)	0.814
(3)	life2	0.001		-0.014	-0.004	-0.003	-0.003	77,170
		(0.69)		(-5.03)	(-2.01)	(-6.39)	(-5.31)	0.822
(4)	life2		-0.017	-0.014	-0.004	-0.003	-0.003	76,058
			(-2.60)	(-4.88)	(-1.87)	(-6.12)	(-5.39)	0.823
(5)	life3	-0.010		0.012	0.007	0.001	0.004	77,170
		(-6.85)		(4.31)	(3.47)	(2.39)	(7.20)	0.726
(6)	life3		-0.014	0.013	0.007	0.001	0.004	76,058
			(-2.24)	(4.47)	(3.27)	(2.36)	(7.11)	0.726
(7)	life4	0.002		0.010	-0.010	-0.004	0.002	77,170
		(1.85)		(6.21)	(-6.90)	(-12.1)	(6.03)	0.508
(8)	life4		0.001	0.011	-0.010	-0.004	0.002	76,058
			(0.24)	(6.00)	(-6.62)	(-12.0)	(6.11)	0.510
			Panel B: Text-Based International Growth Opportunity Shock					
(1)	life1	0.008		-0.009	0.007	0.006	-0.003	77,170
		(7.05)		(-3.73)	(3.48)	(11.0)	(-8.41)	0.812
(2)	life1		0.056	-0.010	0.006	0.006	-0.003	76,058
			(10.9)	(-3.92)	(3.15)	(10.7)	(-8.40)	0.815
(3)	life2	-0.005		-0.014	-0.004	-0.003	-0.002	77,170
		(-3.75)		(-5.03)	(-1.79)	(-6.31)	(-5.09)	0.822
(4)	life2		-0.041	-0.014	-0.004	-0.003	-0.003	76,058
			(-7.04)	(-5.01)	(-1.64)	(-5.80)	(-5.16)	0.823
(5)	life3	-0.002		0.013	0.007	0.001	0.004	77,170
		(-1.88)		(4.39)	(3.24)	(2.50)	(7.25)	0.725
(6)	life3		0.000	0.014	0.007	0.001	0.004	76,058
			(0.06)	(4.52)	(3.28)	(2.32)	(7.13)	0.726
(7)	life4	-0.001		0.010	-0.010	-0.004	0.002	77,170
		(-0.71)		(6.19)	(-6.78)	(-12.1)	(6.06)	0.508
(8)	life4		-0.016	0.010	-0.009	-0.004	0.002	76,058
			(-3.85)	(5.90)	(-6.50)	(-11.8)	(6.22)	0.510

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.

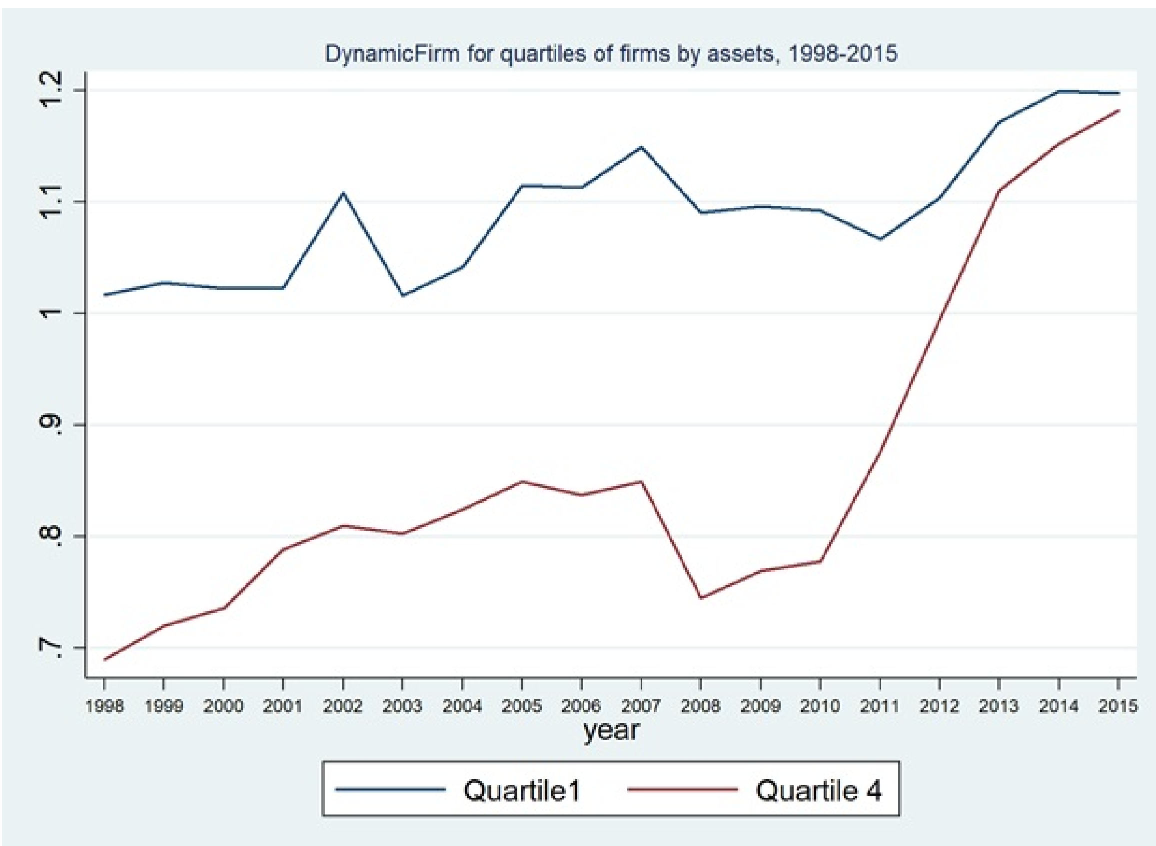
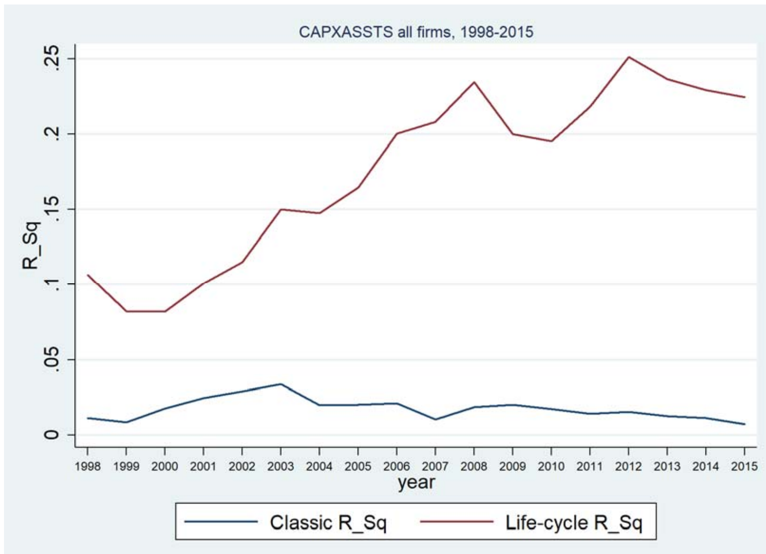


Figure 3: Plot of the R^2 of the annual cross sectional regressions in Tables 7 and 8. The Basic Classic model does not adjust for differences in the investment-Q relationship for different values of the life variables. The Conditional model adjusts for the level of the Life variables and their interaction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

Panel A – CAPX/Assets



Panel B – R&D/Assets

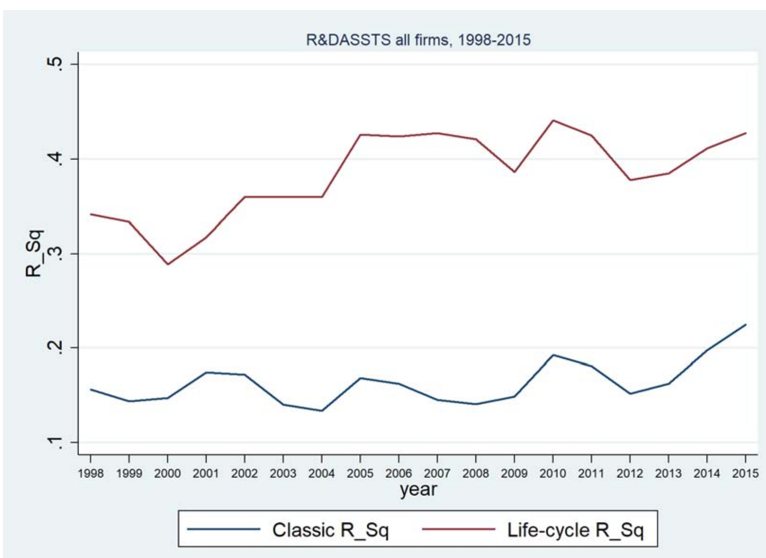


Figure 4: The figure displays the adjusted R^2 in time series from annual OLS regressions where the dependent variable is CAPX/assets, and Tobins Q is the key RHS variable. We also include controls for log assets and log firm age. All RHS variables are ex ante measurable from year $t-1$. The figure displays results from this regression run on three samples: full sample (top), the subsample with above median TNIC total similarity (middle), and the subsample with below median TNIC total similarity (bottom). Within each aforementioned sample, we also separately report results for further subsamples based on above and below median firm dynamism. Dynamism is $Log[\frac{Life1+Life2+Life4}{Life3}]$. All subsamples are formed based on annual median breakpoints.

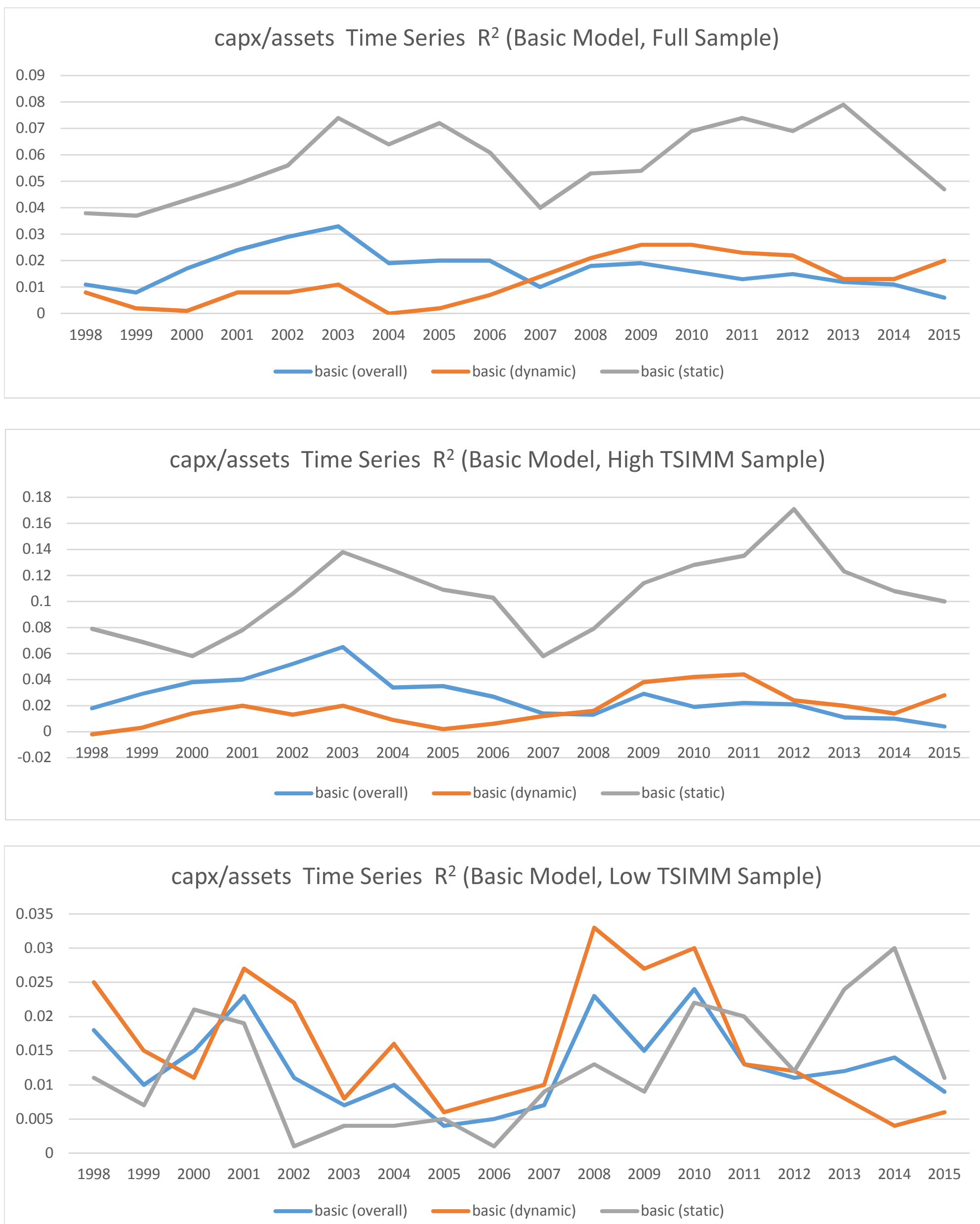


Figure 5: The figure displays the adjusted R^2 in time series from annual OLS regressions where the dependent variable is CAPX/assets, and the four life cycle variables and their interaction with Tobins Q are the key RHS variable. We also include controls for log assets and log firm age. All RHS variables are ex ante measurable from year $t-1$. The figure displays results from this regression run on three samples: full sample (top), the subsample with above median TNIC total similarity (middle), and the subsample with below median TNIC total similarity (bottom). Within each aforementioned sample, we also separately report results for further subsamples based on above and below median firm dynamism. Dynamism is $Log[\frac{Life1+Life2+Life4}{Life3}]$. Median breakpoints are formed annually.

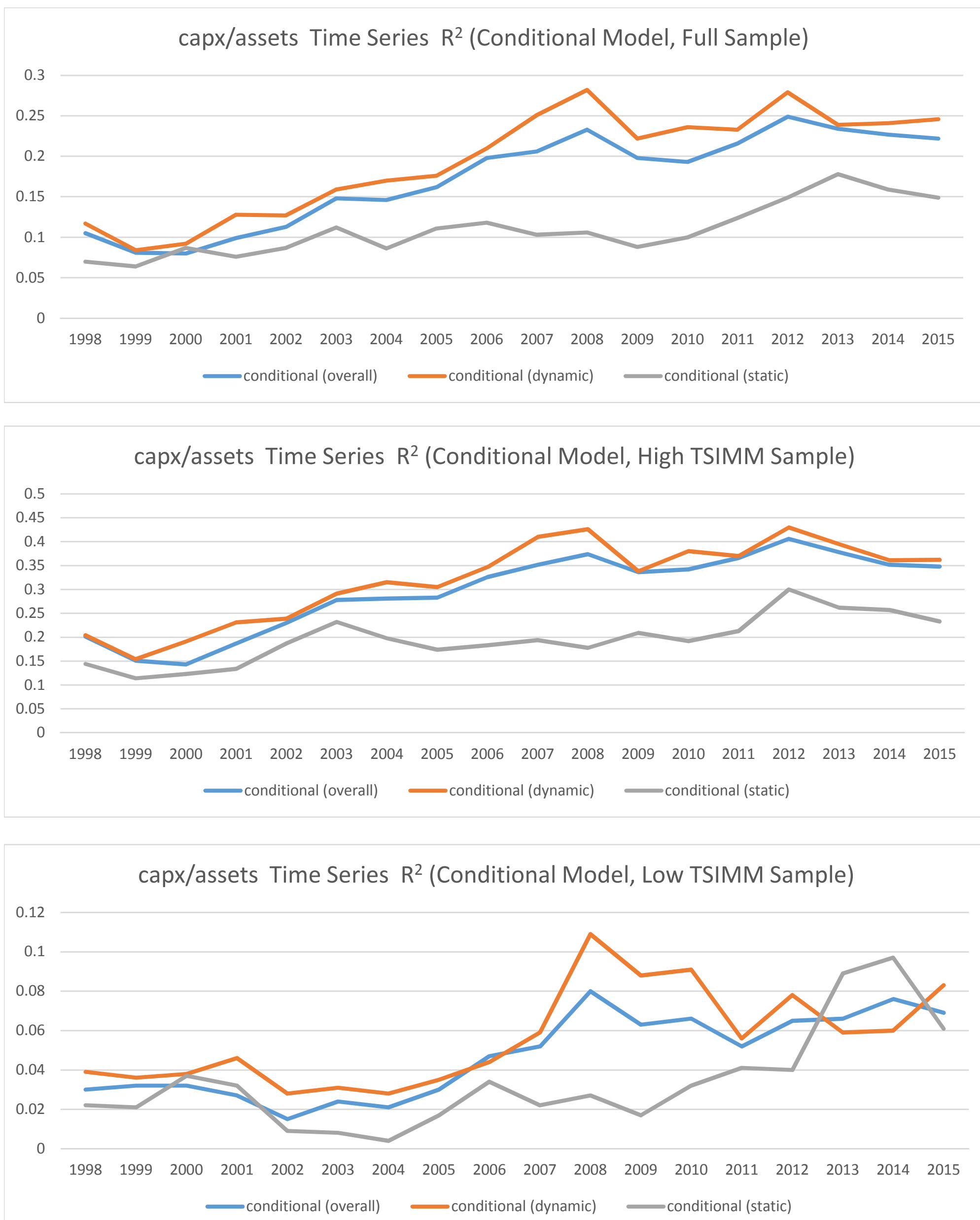


Figure 6: The figure displays the adjusted R^2 in time series from annual OLS regressions where the dependent variable is CAPX/assets, and in each figure (based on a subsample discussed below) we report results for two different sets of RHS variables. The first (the "cond noQ" model) includes the four life cycle variables and controls for log assets and log firm age. The second (the "conditional" model) includes all variables in the first set and adds the four live variable interactions with Tobins Q. The figure displays results from both models for four samples: above median dynamism and above median TNIC total similarity (top), below median dynamism and above median TNIC total similarity (second), above median dynamism and below median TNIC total similarity (third), and below median dynamism and below median TNIC total similarity (bottom). Dynamism is $Log[\frac{Life1+Life2+Life4}{Life3}]$. Median breakpoints are formed annually.

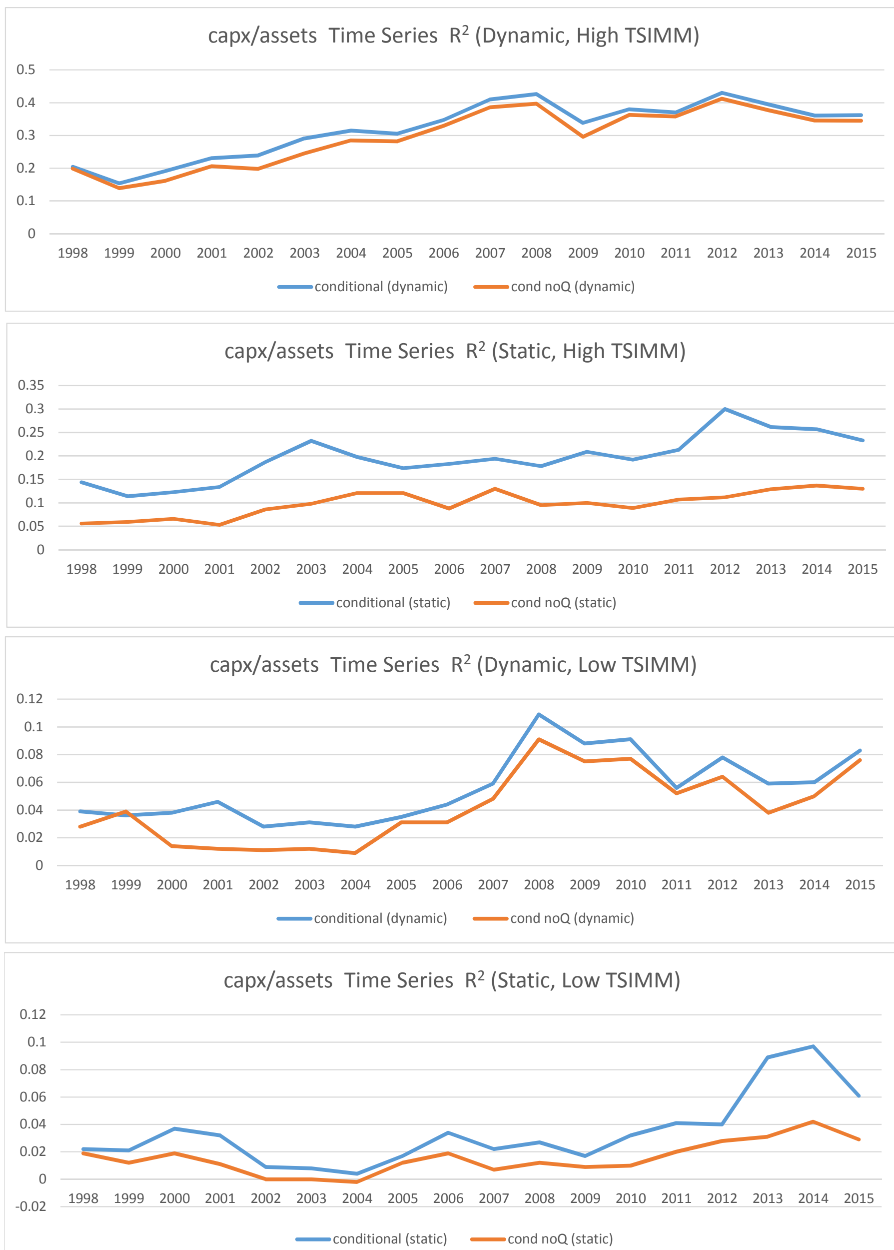


Figure 7: The figure displays the adjusted R^2 in time series from annual OLS regressions where the dependent variable is CAPX/assets, for three models. The first is the basic model, which includes Tobins' Q and the controls for log assets and log firm age. The age-quartile-based life cycle conditional model is based on first sorting firms into quartiles in each year based on firm age. This model adds four dummies to the basic model (one indicating each of the four age quartiles) and replaces the Tobins' Q variable with the four dummy variable interactions with Tobins Q. The text-based life cycle conditional model first adds the four text-based life cycle variables (life1, ..., life4) to the basic model, and then also replaces the Tobins' Q variable with the four interactions between these life cycle variables and Tobins' Q.