# Product Life Cycles in Corporate Finance

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**ABSTRACT**

We develop a novel 10-K text-based model of product life-cycles and examine firm investment policies. Conditioning on the life cycle substantially improves the explanatory power of investment-Q models. The improved models reveal that investment follows a pecking order through the life cycle. Firms initially focus on R&D, which also becomes very sensitive to Q. CAPX emerges second. Acquisitions then arise as firms mature, and divestitures emerge as firms enter decline. At the aggregate economy level, major shifts away from mature life cycle stages and toward dynamic stages explain much of the disappearing CAPX anomaly, and why the explanatory power of Q-models is increasing over time. International competition is a likely catalyst for these changes.

# 1 Introduction

In recent years, U.S. public firms have undergone major compositional and internal changes. 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 increases in market concentration.[2] These developments prompt the question: how do these changes affect firms' investment policies?

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 measure firm-level changes in exposure to product life cycle stages, and link these exposures to investment decisions. The result is an extension to the standard empirical Q-theory model of investment, which is based on the simple idea that firms invest until the present value of marginal cash flows exceeds the cost of investment. This approach yields five major conclusions, which are robust using the intangible capital-adjusted Q from Peters and Taylor (2017), and measurement error corrections from Ericson and Whited (2012).

First, our text-based product life cycle model reveals a corresponding pecking order of investment intensities and sensitivities to Q. Firms with exposure to the product innovation stage invest heavily in R&D, and they invest even more intensively when their market valuations rise. As firms transition to the process innovation stage of the life cycle, they invest heavily in CAPX, and CAPX also becomes more sensitive to Tobins' Q. Firms with products entering the mature stage then focus on acquisitions, which also become sensitive to Q. The investment pecking order thus favors organic investment before inorganic investment such as acquisitions. Finally, firms with products entering decline are more likely to be targets and sell their assets.

[1]See Doidge, Kahle, Karolyi and Stulz (2018), who show that fixed assets have fallen from 34% to 20% of total assets between 1975 and 2016 and average capital expenditures have 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).

This reveals a broad pattern of asset transfer from late stage firms to more youthful and healthier mature firms. Interestingly, when Q rises for firms facing decline, they shift focus away from selling assets and toward being acquirers.

Second, conditioning on firm exposures to life-cycle stages dramatically improves the performance of investment-Q models. The adjusted $R^2$ of the conditional CAPX-Q model is roughly 2x to 4x higher overall, and it also increases strongly throughout our sample.[3]

Third, we document a major shift in U.S. corporations that is new to the literature. During our sample period from 1998-2015, firms strongly abandon the mature stage of the life cycle in favor of more youthful and dynamic product market strategies. We refer to this trend, which is strongest for larger firms, as the "Rise of the Dynamic Firm". We also find that this new stylized fact is strongly related to the well-known decline in capital expenditures spending during our sample (see Gutierrez and Phillipon (2016) for example). In particular, this drop is much smaller for firms with above median dynamism (24% decline in CAPX during our sample) than for static firms (52% decline). These findings are even more stark for firms with above-median levels of competition, where CAPX only declines by 14% for dynamic firms versus 51% for static firms. Understanding that the decline is mostly due to firms with high exposures to product lines in the mature stage of the life cycle suggests that much of the decline might be due to mature products simply maxing out their potential in the global market and not needing further investment.

Fourth, we show that the level of competition is a determinant of how firms with different exposures to the product life cycle respond to investment opportunities. Broadly, in competitive markets, firms that are more dynamic (those focused on product and process innovation) respond most strongly to Q. However, novel strategies for firms in less competitive markets also emerge. For example, when these firms have increased exposure to declining products, the R&D and acquisition investments

[3]For brevity, we henceforth refer to adjusted $R^2$ as just $R^2$. This increase is stark, as $R^2$ rises from 10.3% to roughly 20% during our sample period. This increase reinforces the findings of Gutierrez and Phillipon (2016) and Andrei, Mann, and Moyen (2018).

of dynamic firms in less competitive markets become highly sensitive to Q. 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, firms in the more innovative life cycle stages transition 1-2 stages toward more mature stages. Firms with an ex-ante focus on the product innovation stage transition to maturity, and in some cases, 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 transition 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 long term consequences of major shocks. In particular, such shocks can reduce focus on innovative products for prolonged periods of time.

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 global 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).

Although there are some noteworthy exceptions (Ericson and Whited (2012) and Peters and Taylor (2017) for example), decades of empirical research have had to rely on highly aggregated measures of investment opportunities such as ratios of market to book values. A critical issue is that such ratios treat firms as homogeneous and do not provide metrics for predicting the differences in the investment by firms at different life stages and facing different market constraints. More recently, Peters and Taylor (2017) have argued that the calculation of Tobin's Q should be updated to directly incorporate estimates of firms' intangible capital. We discuss their approach below, and note that our approach is complementary to theirs. In contemporaneous work, Andrei, Mann, and Moyen (2018) have proposed a learning model in which investors don't observe but infer the firm's profits. In their model, the explanatory power of the simple Q equation is higher for more R&D intensive industries, which also can shed light on the increasing explanatory power of Q equations over time.

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 described 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 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.[4]

We validate our life cycle model by demonstrating a strong relation between our variables and firm age and also to changes in the firm's product portfolio. We find that, even after including firm fixed effects, both product and process innovation stages 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 grows when the firm is in the product innovation stage of the life cycle, and shrinks when the firm is in the declining stage. Product description growth is not strongly related

[4]As we discuss below, our product-life cycle approach differs from firm-level life-cycle studies, such as Loderer, Stulz and Waelchli (2016), where firm age is the principal state variable.

to process innovation or maturity. These results are strongly consistent with the product life cycle classification in Abernathy and Utterback (1978).

The novel investment and acquisition patterns we document are not possible to observe using simple life cycle proxies such as firm age, which does not contain adequate dimensionality to fully observe these sharply non-linear shifts in investment opportunities across the 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, some shocks accelerate the aging process. In other cases, shocks induce firms to transition in reverse toward more youthful life cycle stages. Because our results cannot be obtained using age alone, our findings are novel given the existing literature on life-cycles.

Overall, our results suggest that understanding a firm's exposure to 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, the effect of macro shocks and the economic effects of heterogeneous product markets.

# 2 Overview and Related Literature

Creating value in a product market often requires going through a set of predictable stages in which the relation between Q and different types of investment changes. For example, consider a new commercial airliner manufacturer. Initially, the firm will invest on design and development. Over time, the firm will shift investment to plant and process efficiency. Thereafter, the mature firm's value will come from sales in a continuous and stable fashion. Finally, as new competitors arise, the focus will be on supporting products still in service and phasing out obsolete models.

Managers can create value in each stage, but such strategies are state-specific and entail different relations between Q and investment in product development, sales, and physical plant. In some stages, the relation between Q and a given form of investment can even be negative, as a high Q might signal an optimal shift away from that investment and toward another.

Our analysis of the relation between Q and investment builds directly on Abernathy and Utterback's (1978) highly-cited classification of product life-cycle stages. 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 product-specific stages as given, and further argue that a firm is a portfolio of products, each potentially being in a different stage of the life cycle. [5] Because each project in a firm's portfolio might be in a different stage, we measure a firm's total exposure to each stage separately, and do not classify the firm as a whole as being in a particular stage. Over time, each component might increase or decrease in response to competition and shocks.

Our paper is consistent with the approach in Jovanovic (1982), who argues that young firms start off with unknown ability to exploit growth opportunities. Such a firm's investment and financing decisions differ from those of other firms. Subsequent theory has examined related implications as firms age through the lens of information asymmetry or managerial and investor learning about the firm's potential over time. We argue that firm evolution involves more than information revelation over time, but also a transition through a series of states.

Our paper is also related to recent work on the relation between firm age, life cycles, and firm performance. Loderer, Stulz and Waelchli (2016) argue that, as firms age, they become more rigid and less able to optimally respond to growth opportunities.[6] Product market competition slows this process whereas investor

[5]Klepper (1996), and Klepper and Thompson (2006) suggest that industries consist of submarkets, which the firm can enter. We posit that participation in each submarket can be viewed as a distinct project and that each cycles through the Abernathy and Utterback stages.

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

monitoring speeds aging as firms must prioritize investor relationships. Arikan and Stulz (2016) show how firms' acquisition activity follows a U-shaped pattern with respect to age. We find many results that are consistent with these studies: age is relevant empirically and life cycle effects are pervasive. In a companion paper, we also find that issuance and investment are inter-related, reinforcing the need for cash as a key issuance motive (see DeAngelo, DeAngelo and Stulz (2010)). However, we also show that a comprehensive model of product life cycles, aggregated to the firm level, generates many novel and economically large findings.

Much of the empirical analysis is motivated by the Q-theory of investment (Hayashi (1982)). This theory predicts that the firm's investment opportunities can be measured by the ratio of the firm's market value to the cost of reproducing the firm's assets.[7] The Q-theory model has been widely studied in Finance, both in structural models such as Hennessy, Levy, and Whited (2007), and in reduced-form contexts such as Chen and Chen (2012), Erickson and Whited (2000), Peters and Taylor (2017), and Harford (2007). Given assumptions about firm homogeneity and competition in the market for outputs and inputs, the usual relations between investment and Q arise theoretically. One maintained assumption is that there exists a positive relation between future cash flows and ex ante capital stock. However, the relation between Q and a particular capital asset is more complex in practice. For example, 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 inefficient operations. Scholars agree on such variation, but such cases are not reflected in the workhorse model due to tractability. Our paper provides a complete life cycle based empirical framework for quantifying this heterogeneity.

Building on work by Grullon, Larkin, and Michaely (2016), Mongey (2016), and Bronnenberg et al. (2012) showing increases in concentration in U.S. industries over time, and increases in price-cost mark-ups (Nekarda and Ramey 2013), Gutierrez and

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

Philippon (2017) argue that increases in market power weakened the investment-Q relationship. For example, if market power is maintained by restricting output, its rise should be associated a rise in Tobin's Q and a drop in investment.[8] Our approach differs as we quantify the firm's focus on each of the life cycle stages in Abernathy and Utterback using unique text-based firm-specific measures, and we explore their link to investment and Q.

Our paper is also related to the growing literature examining large-scale changes in US firms over the last twenty years. Hoberg and Moon (2017) document an increase in offshoring, Rajan and Wulf (2006) and Gudaloupe and Wulf (2007) show that competitive pressure affects the firm's firm's organizational structure, reporting relationships, and tendency to engage in R&D (see also Autor et al 2016).[9] Using Census data, Magyari (2017) shows that US firms exposed to Chinese import competition shift resources into R&D and service production. Other studies suggest that recent increases in firm inequality manifest in differences in productivity, rates of return and labor compensation (Bloom (2017), Frick (2016)). More broadly, recent literature also focuses on how management characteristics and style affect firm performance.[10] Our study suggests that some of these changes and some management practices might be related to life cycle shifts.

# 3 Data and Methods

Our new life cycle variables derive purely from publicly available 10-K text. Although our textual queries can be programmed using standard languages and web-crawling techniques, for convenience, we use text processing software provided by metaHeuristica LLC. This software has pre-built modules for fast and highly flexible querying,

[8]Note that while this argument is intuitive, it is not obviously correct. For example, extra capacity might be required to punish deviations from a collusive equilibrium, as discussed by Maksimovic (1988).

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

[10]See Bertrand and Schoar (2003), Prez-Gonzlez (2006), Bennedsen et al. (2007), Malmendier, Tate, and Yan (2011) and Levine and Rubinstein (2017). Bloom and Van Reenen (2007, 2010), Bloom et. al. (2013) explore related heterogeneity in management practices.

while producing output that is easy to interpret.[11] For example, many of the variables used in this study are constructed by simply identifying which firm-year filings contain a statement indicating the maturity of its product portfolio.

## 3.1 Data

Our sample begins with the universe of Compustat firm-years with adequate 10-K data available between 1997 and 2015. After further limiting the sample to firm-years with machine readable 10-Ks (both current and lagged), non-missing data on operating income and Tobins Q, 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 using metaHeuristica and covers all filings that appear as "10-K," "10-K405," "10-KSB," or "10-KSB40." We query each document for text pertaining to life cycles, fiscal year, filing date, and the central index key (CIK) and link each 10-K document to the CRSP/COMPUSTAT database using the central index key (CIK), and the mapping table provided in the WRDS SEC Analytics package.

## 3.2 The Product Life Cycle

Our goal is to use direct textual queries to identify the life cycle state of a firm's product portfolio. This "anchor-phrase" method has been used in past studies including Hoberg and Maksimovic (2015) and Hoberg and Moon (2017). Our proposed product life cycle has four states: (1) product innovation, (2) process innovation, (3) stability and maturity, and (4) product discontinuation. For parsimony, we will refer to these states as Life1, Life2, Life3, and Life4, respectively. Critically, our research requires that firms discuss these stages in their 10-K. Here we point readers to Regulation S-K, where Item 101 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 such text would indicate a firm with

[11]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.

a high product portfolio loading on the product innovation stage. Regarding process innovation, the same disclosure rules require the firm to disclose its results from operations, of which discussions of the costs of production (and reducing them) are a significant component of MD&A. A firm in the third stage, stability and maturity, should be characterized by discussions focused on continuation and market share, but without reference to product or process innovation. Finally, a firm in the fourth state will discuss obsolescence and product discontinuation.

We empirically model the stages of a firm's product portfolio as a four element vector {Life1, Life2, Life3, Life4}, such that each of the four elements is bounded in [0,1], and the sum of the four components is unity. We expect firms to have non-zero loadings on more than one of these stages in any given year, and the relative intensities of each stage indicate the firm's product portfolio exposure to the cycle. For example, a firm with a vector {.6,.3,.1,0} would overall be seen as earlier in the life cycle than a firm with weights {.1,.3,.3,.3}. However, both firms have some exposure to product innovation and maturity.

To measure the firm's loading on the first stage "Life1", 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 "Life2", 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:*** cost 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 "Life3", we require three word lists. A firm's 10-K must contain at least one word from each of the first two lists (List A and List B below), and must not contain any words from the third list below (List C). The exclusion ensures that Life3 is characterized as the static state of product maturity as the exclusion list is based on the union of the other three dynamic life cycle stages.

***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 the firm's loading on "Life4", 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

The above queries result is a count of the number of paragraphs that hit on each of the four stages Life1 to Life4. We then compute our firm-year life cycle exposure vector by dividing each of the four individual paragraph counts by the total paragraph counts of the four. The result is a four-element vector for each firm-year $\{Life1, Life2, Life3, Life4\}$ that sums to one. All four exposures are also non-negative and are bounded in $[0, 1]$.

Although we do not assign it a stage number, we also examine the absorbing state of delisting ("LifeDelist"). Specifically, we focus on delistings due to poor performance, which includes CRSP delisting codes in the interval 520 to 599. We also measure 10-K document length ("Whole 10-K Size") as the natural logarithm of the number of paragraphs in the given firm's 10-K as identified by the metaHeuristica system. Our results are not highly sensitive to including or not including this variable 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 (TNIC) developed in Hoberg and Phillips (2016) to measure market structure. We do so because this classification is updated dynamically each year, and is based directly on product market text. There are three benefits: (1) the TNIC network is intransitive and customized to each firm-year observation as is the case for our life cycle variables, (2) it is more informative, and (3) it is updated to reflect dynamic changes in the product market. In contrast, Herfindahl indices based on SIC or NAICS codes are do not reflect changes in the product market, and do not provide information on product differentiation. Concentration ratios are also backward looking as they use already-realized sales from financial statements.

We first note that TNIC can be expressed as a network where each pair of firms has a known product similarity. We thus follow Hoberg and Phillips (2016) and compute competitive intensity as the total product similarity between a given firm and all of its rivals using the baseline TNIC-3 classification (this classification is calibrated to be as granular as three-digit SIC codes). Intuitively, a firm with low total similarity rarely encounters a competitor in its product market network indicating possible monopoly-like rents. A firm with a high total similarity interacts intensively with competitors. The micro foundation for these measures of competition obtains from the seminal literature on product differentiation dating back to Chamberlin (1933) and Hotelling (1929). Although we report results using our total similarity measure, we also note that using NAICS-3 HHIs generates similar results, which are still highly significant although slightly weaker in magnitude.

### 3.4 Measuring Q

The literature has developed multiple measures of Tobin's Q, with each perhaps being ideal for different applications. We compute Q following Gutierrez and Philippon (2017) as the market value of the firm divided by book assets. We are ultimately agnostic on the broader debate regarding which Q is most broadly "the best". Instead, our goal is to choose a method for Q that is most consistent with our goal of testing product life cycles over a broad array of investment policies.

Recently, Peters and Taylor (2017) have augmented investment functions using estimates of non-tangible capital to provide measures of Q that take into account that R&D and branding expenditures have build capital. Specifically, their formulation adds estimates of investment in intangible capital to the firm's investments in fixed assets and an estimate of the stock of intangible capital to the firms stock of tangible capital. Investment in intangible capital is assumed to consist of 20% of the firm's realized expenses on Selling, General, and Administrative (SG&A) expenses and 100% of its R&D expenses in each year. Stocks of intangible capital are then obtained as the depreciated accumulated SG&A and R&D.[12] This has many advantages, but it can also confound interpretation in our context. For example, we expect investment in R&D and SG&A to vary systematically over the life cycle. For example, high SG&A in the early stages might reflect high investment in organizational capital,

[12] Following earlier literature, it is assumed that R&D stocks depreciate at 15% per year and SG&A stocks depreciate at 20% a year. See, for example, Falato, Kadyrzhanova and Sim (2013).

whereas it may reflect high costs of sales in the later stages. Also, a firm with high recent investments in intangible capital or process innovation might transition to maturity, making the adjustments potentially inadequate given expected shifts toward inorganic investment. To avoid any confounding interactions between the product life cycle itself and measures of Q, we estimate Q using the most generic approach as discussed above in our main analysis. However, in our Online Appendix we show that we obtain similar results if we instead use the Q from Peters and Taylor. In the Appendix we also show that our results are robust to the Ericson and Whited (2000) measurement error adjustment.

## 3.5 Policy and Outcome Variables

We examine three investment policies: R&D/assets, CAPX/assets, and the decision to acquire assets inorganically via acquisition. We also examine dis-investment in the form of selling assets as a target. The R&D (XRD) and CAPX variables obtain from COMPUSTAT and we scale by beginning of period total assets (AT). When R&D is missing, we assume it to be zero. All accounting ratios are winsorized within each year at the 1%/99% level. We obtain acquirer and target data using both full-firm and asset acquisition data from SDC Platinum.

## 3.6 Summary Statistics and Correlations

Table 1 displays summary statistics for our 1997 to 2015 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 18.5% of firms sell at least some assets (both acquisition variables include both public and private targets). The average Tobins Q in our sample is 1.55. The average firm in our sample has a profitability ratio of 8.5% relative to sales and 4.9% relative to assets and the average log sales growth is 9.8%.

Panel A of Table 2 reports Pearson correlation coefficients. Because they sum to unity, the Life1 to Life4 variables are negatively pairwise correlated. We also observe that Life1 is negatively associated with firm age (-18.3%) and Life4 is positively associated with firm age (17.4%). This corroborates a primary prediction of the product life cycle theory. Firms generally begin life with a large fraction of their product portfolio in the product innovation stage and end life with product discontinuation and eventual delisting. However, one surprising result is that process innovation (Life2) is positively correlated with age whereas product maturity (Life3) is negatively correlated. Results later in the paper will show that these univariate findings are purely driven by cohort effects, and the ordering of the life cycle states relative to aging becomes very close to the theoretical predictions when we focus on within-firm variation (and control for firm fixed effects). Hence, for any given firm in time series, process innovation precedes product maturity on average.

[**Insert Table 2 Here**]

The table also echoes some of our main pecking order results as firms in different stages of the life cycle focus on very different investments. Life1 firms focus heavily on R&D (51.5% correlation) and Life2 firms focus on CAPX (33% correlation. As we would expect given their product maturity and potential lack of internal growth options, Life3 and Life4 firms correlate negatively with both forms of investment. Life3 firms also have almost zero correlation with sales growth, further affirming the interpretation of this state as maturity.

Acquisitions are positively associated with Life3, indicating that mature firms focus on acquisition-based investment options when as their internal growth options (R&D and CAPX) become exhausted. Life4 firms, in contrast, are negatively correlated with all three forms of investment (R&D, CAPX, acquisitions) and are positively correlated with being targets of acquisitions. Hence, the option to sell and transfer assets externally is one way that declining firms can create value for their shareholders as their products become obsolete.

Panel B of Table 2 reports the autoregressive coefficients of our 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 exposure is stable over time and that movement through the cycle is a relatively slow process.

Figure 1 illustrates how Life1 to Life4 vary over our sample period for large and small firm quartiles (based on total assets, sorted annually). We expect these measures to vary across firms of different size because smaller firms are likely to be young firms focused on launching products, or older firms that have not been able to expand successfully. 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, these firms 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, following the 2008 financial crisis, large firms materially narrow this gap, suggesting that large firms are becoming more entrepreneurial. Also as expected, large firms have higher values of Life2 than small firms. Life2 is also rising over our sample period, indicating that firms are devoting more effort to process innovation.

Figure 1 also shows that the level of Life3 is initially much higher for large firms, but these large firms experience substantial declines in Life3 over time. By the end of our sample, the gap between the large and small firms has essentially closed. Our findings for both Life1 and Life3 thus indicate a major transition for large firms during our sample period that is new to the literature.

Intuitively, values of Life4 increase for all firms during and after the technology bust (2000-2004). Life4 then remains at the elevated levels through the remainder of our sample as the number of firms in our sample declines from 5830 to 4880. The concurrent increase in Life4 and delisting rates are consistent with a heightened level of restructuring, obsolescence and failure by many firms during this period.

Our sharp findings regarding a shift away from the inactive mature stage Life3, and toward the three other more active stages of the cycle is consistent with large firms transitioning from relatively static life cycle strategies to dynamic strategies. These dynamic strategies cover Life1, Life2, and Life4, all of which entail ongoing refinement of product and process portfolios. We summarize this first-order shift of larger firms toward a more dynamic posture over our sample period by combining the four Life measures into a firm dynamism index:

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

Figure 2 shows how this dynamism index changes over time for both small and large firms. At the beginning of our sample, small firms are much more dynamic than large firms. Over time, small firms become slightly more dynamic. However, larger firms become dynamic at a much faster pace and experience a 68% growth in dynamism compared to just 20% for smaller firms. By the end of our sample, large firms have substantially reduced the gap between themselves and smaller firms. We conclude that large firms have undergone a major transformation, especially following the 2008 financial crisis.

**[Insert Figure 2 Here]**

# 4 Validation

Our life cycle measures are derived using direct textual queries via anchor-phrase methodology, which requires key concepts to appear in close proximity. The result is interpretation that is strongly established through texture. Despite this, we believe it is important to stress test new measures and we consider two validation tests. These tests not only test the life cycle interpretation, but also offer a glimpse of the magnitude of the economic content of these variables.

Our first test examines whether the product life cycle of Abernathy and Utterback (1978) can be illustrated using our measures. The central prediction is that, in time series for a given firm, 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. However, 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 over time consistent with the predicted cycle. For completeness in Panel B, we add controls for size, Tobins Q, and document length. We cluster standard errors by firm. The results are presented in Table 3.

[**Insert Table 3 Here**]

The results for the log age variable in Panel A yields support for the Abernathy and Utterback (1978) life cycle. These tests include both firm and year fixed effects, and we observe that Life1 and Life2 are negatively related with firm age and thus appear more often when firms are young. In contrast, Life3, Life4, and Life Delist are more likely to appear when firms are older. This within-firm evidence indicates that product and process innovation are a mainstay for younger firms. Over time, firms transition to stability and ultimately decline. Our inferences are little-changed when we add the additional control variables in Panel B.

The only unexpected finding in Table 3 is that the coefficient for Life2 is more negative than the coefficient for Life1, althoug the difference is more modest in Panel B with the added controls. One explanation is that much product innovation likely occurs when firms are still private, which we do not observe, pushing forward the computed link to firm age. Another explanation is that many young firms face financial constraints and hence need to focus at least some attention on cost cutting and process to conserve liquidity. Hoberg and Maksimovic (2015) and  (2010) show that these younger and more innovative firms indeed appear to suffer more from financial constraints than do other firm types.

Figure 3 illustrates the average of each Life variable as we increase firm age using age percentiles on the x-axis. The leftmost graph for each life variable plots the life variable's raw average, and rightmost graph reports the average net of firm and year fixed effects (within firm variation). The figures illustrate the critical nature of isolating within firm variation, as the relationship between Life2 and Life3 and firm age switches sign across the left and right graphs. These findings also illustrate that there are significant cross-sectional cohort effects in our sample, with older cohorts being more process and manufacturing oriented. This illustrates the importance of including firm fixed effects when making inferences.[13]

**[Insert Figure 3 Here]**

Our second validation test examines if our life cycle measures, particularly Life1 (product innovation) and Life4 (product decline), predict changes in the size of the firm's product portfolio. Following Hoberg and Phillips (2010), our first variable of interest is the logarithmic growth in the size of the 10-K business description from one year to the next. Our prediction for validation is that Life1 should positively associate with product description growth and Life4 should be negatively associated. We include firm and year fixed effects plus additional controls. The results are reported in Table 4. Because the four life variables sum to unity, we exclude Life3 to avoid co-linearity with the intercept. Hence the coefficients on the remaining life

[13]Controlling for the stable part of a firm's disclosure, as is the case when firm fixed effects are included, is also important in light of the finding by Cohen, Malloy, and Nguyen (2018) that even small changes in disclosures are significantly informative about future real outcomes.

cycle variables should be interpreted as whether the dependent variable is higher or lower relative to the average for Life3 firms. We exclude Life3 because it is a stage characterized by stability, making it the most intuitive reference group.

[**Insert Table 4 Here**]

Panel A shows that the product description grows significantly faster when the firm has a high loading on the product innovation stage (Life1), and growth is significantly negative when the firm has high exposure to the product decline stage Life4. The results are highly significant well-beyond the 1% level despite the inclusion of controls for firm age and and firm fixed effects. These results strongly validate our key life cycle variables. Also as predicted, we do not see significant results for Life2 or Life3, as product offerings should not change materially when firms focus on process innovation or maturity.

We also examine the link to Tobin's Q in rows (2) and (3). Here, as in all subsequent tables, Tobin's Q is re-centered at the sample mean prior to running the regressions so that the Life1, Life2, and Life4 coefficients are interpretable as the impact of a one sigma shift in the given variable on the dependent variable for a firm with average Q. As expected, row (2) shows that firms with higher Q experience stronger product description growth. In Row (3), we examine if firms exposed to each stage react to Q differentially. Because Life1 to Life4 sum to unity, we note that replacing the level of Tobin's Q in Row (2) with the four cross terms, allows us to estimate four distinct conditional effects of Q associated with each stage of the life cycle. We find that the positive link between Q and product description growth is primarily attributable to Life1 firms, which thus experience ultra-fast product description growth when their Q is high. Life3 also has some sensitivity to Q and Life2 and Life4 have no sensitivity. We will illustrate later that this is likely because Life2 and Life4 firms have different growth options. For example, Life2 firms with high Q tend to increase capital expenditures as Q increases and Life4 firms tend to increase divestitures.

As an additional test of validation, Panel B of Table 4 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 broad 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, 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 stages.

Overall, we view the evidence in this section as strongly validating the interpretation of our Life cycle 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, which 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 firm product portfolios in the life cycle. For example, do firms mature prematurely following shocks like the financial crisis, or do they focus less on current sales and utilize spare resources on future innovation. We consider two shocks and examine two years (a pre and a post shock year) for each shock. The first is the technology bust, where we consider 1999 and 2001. The second is the financial crisis, where we consider 2007 and 2009. We then examine regressions in which the ex post life cycle state is the dependent variable, and we consider a post-treatment dummy and its interactions with ex ante life cycle exposures. We use the same panel data specification with firm and year fixed effects as we use in later tests, except we restrict the sample to just these two-year comparisons.

[**Insert Table 5 Here**]

Table 5 displays the results and Panel A focuses on the technology bust. Results for the cross term (Shock x Life1) indicate that the technology bust accelerated life cycle transitions in the direction of young to old. Life1 firms transitioned to Life2, Life3 and even delisting faster than in the control year. Life2 firms transitioned faster to Life3, Life4, and delisting. We conclude that the technology bust led many firms to age quickly, in some cases moving two stages down the life cycle. We also find that mature Life3 and Life4 firms shifted some toward process innovation and cost cutting, as cost reduction was likely necessary for long term profitability. These results are intuitive and serve two purposes. First, they further validate our interpretation of the measure. Second, they formally illustrate the real consequences of shocks like the technology bust.

Panel B of Table 5 shows that the financial crisis led to a similar acceleration in aging. Life1 firms shifted toward maturity (Life3) and decline (Life4) and Life2 firms moved toward decline (Life4). As in the technology bust, we also observe more mature firms shifting some toward process innovation and cost cutting. Yet we also note one finding that is unique to the crisis: firms in ex ante decline (Life4), on average, also shift toward Life1, indicating that firms in decline can become opportunistic. One interpretation is that declining firms were able to take advantage of the dramatic aging of the innovative firms during this time. As we show later, this shift is driven at least in part by declining firms increasing their acquisition rate, and hence the more innovative products were likely acquired. This is also consistent with existing evidence of innovative firms facing financial constraints during the crisis

(Hoberg and Maksimovic (2015)), and with declining firms using liquidity in the form of retained earnings and asset sales to purchase assets from these constrained firms. Further research on life cycle reversals and their timing is likely to be fruitful.

We next explore whether the major changes in international competition and international growth opportunities can help to explain the increases in firm dynamism we reported earlier. This hypothesis is motivated by the fact that international shocks are a form of market disruption, and optimal responses might entail shifts in a firm's life cycle disposition. 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". We measure international growth opportunities as 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 }.

We regress ex post life cycle variables on ex ante values of international competition and international growth options as defined above. In addition to firm level measures of international competition and growth, we consider less endogenous averages of both over distant TNIC industry peers. Shocks to distant product market peers are plausibly more exogenous for the same reasons that the market return is often used as an instrument: any one firm cannot influence the overall market but must accept the consequences of the market's movements. We define distant peers as those in a firm's TNIC-2 industry but not in a firm's TNIC-3 industry. All RHS variables are ex ante measurable in year $t-1$ and all specifications include firm and year fixed effects and standard errors are clustered by firm.

[**Insert Table 6 Here**]

Panel A of Table 6 displays the results. Ex ante increases in international competition are associated with significantly lower ex post exposures to Life3, and higher ex post exposures to Life1. These findings, especially when driven by distant peers, imply that international competition likely induces firms to become more innovative and dynamic. This is consistent with improving product offerings to be competitive on the more contested global stage.

Globalization not only increases foreign competition. It also brings new international growth opportunities to domestic firms seeking expansion. Hence Panel B of Table 6 examines international growth options. As expected, we find that increases in these growth options is associated with a strong shift toward the innovative life cycle stage, Life1. These results are stronger than those based on international competition in Panel A. One reason why international growth options might induce a shift toward product development is that international consumers might favor different product features, which need development. Also, the global market might demand higher quality product offerings given the more aggressive competition on the international stage.

We conclude that although firms follow the life cycle transitions on average, they do not progress deterministically down the life cycle. This is why firm age is far from ideal as a proxy for life cycles. We also 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, declining firms find opportunities to revert toward innovative stages. Finally, our findings on globalization indicate a shift toward firm dynamism, which is likely instrumental in explaining the major shift toward dynamism we reported earlier.

# 6 Investment and the Product Life Cycle

In this section, we consider panel data regressions with firm and year fixed effects to formally examine how firms' investment decisions change with the product life cycle. Table 7 reports results from investment-Q regressions. The dependent variable is R&D/assets (Panel A) and CAPX/Assets (Panel B). The RHS variables include ex-ante life cycle variables, interactions with Tobins Q, and size plus age controls. As noted earlier, Tobin's Q is re-centered at its sample mean so that the life cycle variable coefficients are interpretable as the impact of a one sigma of the given variable on the dependent variable for a firm having an average Q.[14] The Online Appendix shows robustness to (1) defining competition using the NAICS and TNIC-3 HHI instead of TNIC total similarity, (2) using Tobins Q as measured by Peters and Taylor (2017), (3) using Tobins Q as measured by market value scaled by PP&E, and (4) using the Erickson and Whited (2017) measurement error correction. In the Online Appendix we also report specifications with lagged dependent investment variables and their interactions with Q as additional explanatory variables, estimated both using least squares and the Blundell and Bond (1998) correction for the correlation between lagged dependent variable and the fixed effect.

[**Insert Table 7 Here**]

We report results for the whole sample, and subsample splits based on several dimensions of interest. For example, to examine whether life-cycle effects differ across firms in competitive and less competitive markets, as motivated by Gutierrez and Phillipon (2016), we split the sample based on annual medians of product market competition (based on TNIC-3 total similarity). As discussed earlier, we use this measure of competition because, unlike HHIs, it dynamically captures changes in the product market over time, and 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. This distinction is important because innovative firms often have negligible sales.

We also split the sample into dynamic and less dynamic ("static") firms, and young versus old firms. Firm age is relevant because it is the central life-cycle variable considered in Loderer, Stulz and Waelchli (2016). Although we also control for firm age in all regressions, these splits allow for interactions and non-linearities to manifest.

Panel A of Table 7 focuses on R&D/assets. As expected, we find that Life1

[14]Thus, our interpretations are conservative. In unreported regressions, we obtain even sharper results for firms at the 75th percentile of Q, where the incentive to invest is even higher.

firms invest more heavily in R&D relative to other firms and their Q-sensitivity is also positive and significant throughout the subsamples. However, unlike any other studies, we also find that *only* Life1 firms have positive Q-sensitivity to R&D. The other three stages are either insignificant or negative. Because only 25% of all products are in Life1 (See Table 1), this implies that Q-sensitivity to R&D is highly conditional on the life cycle. More starkly, the Q sensitivity of Life3 firms is negative and significant in the whole sample and also in some sub-samples. This suggests that when Life3 firms experience a high Q, one likely should expect increases in other value-adding investments and not R&D specifically. Indeed, as we report later, these firms tend to increase CAPX, and especially acquisition activity, when their Q increases.[15] Turning to CAPX in Panel B, we also find that Life1 firms invest more than Life3 firms. Life2 and Life3 firms invest similarly, and Life4 invest less. Life2 firms are most sensitive to Q, and Life3 firms are also significantly sensitive.

Table 8 examines investment in acquisitions and dis-investment in the form of assets sales. Panel A examines acquisitions and we find that Life3 firms do the most acquisitions (as the other Life variables are generally negative and Life3 is the comparison group), and Life3 firms are also the most sensitive to Q and do more acquisitions when Q is high. Life2 and Life4 firms are somewhat sensitive to Q, and Life1 firms are negatively sensitive. These results once again reaffirm our main conclusion that the nature of a firm's response to Q is highly dependent on its life cycle stage. The high sensitivity of Life3 firms to increased Q is consistent with the investment pecking order, as Life1 firms invest in R&D, Life2 and Life3 firms invest in CAPX, and more mature Life3 firms focus on inorganic investment in the form of acquisitions. Life4 firms do fewer acquisitions on average, although they have a positive Q-sensitivity. This suggests that increased market values for declining firms signals likely acquisitions as their best investment option to potentially shift toward more youthful and sustainable life cycle stages.

[15] In unreported tests based on large versus small firm subsamples, we find that small Life4 firms are insensitive to Q whereas large firms increase R&D when Q increases. This suggests that the end-stages of a project may signal the end of a small firm, whereas larger firms are able to substitute into more valuable early projects (Guedj and Scharfstein (2001)).

**[Insert Table 8 Here]**

Panel B shows the relation between asset sales (targets of acquisitions) and life cycle stages. Our main result is that Life4 firms, facing decline, experience a higher rate of asset sales. Turning to Q-sensitivity, these same Life4 firms divest fewer assets as Q increases. Hence asset sales likely signal the least desirable outcome for firms in decline, and a higher market value indicates a shift away from sales and toward acquisitions as noted earlier for these firms. This suggests that the investment pecking order eventually faces a dry-well problem. After exhausting organic growth options in Life1 and Life2, and inorganic growth options in Life3, it follows that Life4 firms have few remaining growth opportunities. Hence their value maximizing strategy is to dis-invest assets through sales unless new opportunities emerge, allowing the firm to shift to more youthful stages.

We conclude that investment follows a rough pecking order through the product life cycle, and this pecking order strongly determines the relevance of investment-Q models across various types of investment. Life1 and Life are associated with organic investment in the form of R&D and CAPX. The earliest Life 1 stage firms furthermore have negative Q sensitivities to acquisitions, suggesting that investors only reward Life1 firms when their investment options load more on R&D. Life2 firms focus on CAPX and some M&A Q sensitivity. As firms mature to Life3, we observe a sharp rise in M&A and also Q sensitivity to both CAPX and M&A. We also observe negative sensitivity to R&D, which is quite remarkable given the existing literature. Yet this result likely reflects the intuition that a mature firm initiating R&D likely reflects defensive strategies following competitive shocks or market disruption, and hence does not convey good news. Finally, Life4 is associated with increased divestiture, and significant positive sensitivities to CAPX and acquisitions. These pecking order relationships are qualitatively stable across subsamples and are consistent with the economic intuition of the Abernathy and Utterback (1978) stages.

## 6.1 Economic Magnitudes

In this section, we report the economic significance of our earlier findings. Our key findings indicate that predicted values of CAPX, R%D, and M&A activity depend both on the stage of the life cycle, on realized values of Tobin's Q, and interactions between both. Because these variables differ across subsamples, we focus on methodology that is flexible enough to more fully illustrate this variation. Given the importance of competition and dynamism in our earlier results, we focus on five samples: the full sample, dynamic and competitive, dynamic and low competition, static and competitive, and static and low competition. The four subsample permutations based on dynamism and competition are formed using independent annual sorts into above and below median values of our dynamism measure and TNIC-3 total similarity.

Table 9 reports the economic magnitudes both for our life cycle variables alone, and also for the sensitivity to Tobins Q. For each investment policy and subsample, the first column reports the average value of the given policy variable in the given subsample. The spread in Tobins Q across the 25th, 50th, and 75th percentile values are displayed in the second to fourth columns for each subsample. In the later columns, we consider further subsets based on the life stage and Tobins Q to illustrate the impact of Q-sensitivity. The next 8 columns thus show the average value of the dependent variable for 8 subsets of observations as follows. The first two columns are based on the subset formed by sorting observations into annual quartiles based on the value of Life1, and then taking only observations in the highest quartile, and then conducting a second conditional sort into quartiles based on Tobins Q. The first and second columns thus report the average investment for high Life1 quartile firms having the lowest and highest Tobins Q within each subsample, respectively. The remaining six columns are formed analogously for low and high Q sorts of high Life2, Life3, and Life4 firms. The last two columns are subsample averages based on single sorts based on annual Tobins' Q alone (these reflect results for the basic model used in the existing literature). The first reports the average of the dependent variable for the low Q quartile and the latter for the high Q quartile.

**[Insert Table 9 Here]**

The first major finding is that dynamism and competition are both important in predicting investment and acquisitions. For R&D, and CAPX, the dynamic and high competition subsample is most active, and the sample wide averages increase from 0.047, and 0.051 in the full sample, to 0.101, and 0.071 in the dynamic and competitive subsample, respectively. For acquisitions, the full sample average increases from 34.4% to 40.1% in the diametric opposite static and concentrated subsample. These results illustrate the investment pecking order, and the focus on organic investment in the younger and more competitive subsamples, and the focus on acquisitions in the later life cycle stages and more concentrated markets. These differences are also economically large and affirm the relevance of the product life cycle as suggested by Abernathy and Utterback (1978), who also suggest that early "fluid" stages of the product life cycle are more competitive. This also supports the use of R&D to "escape competition" hypothesis discussed in Aghion et al (2005).

We find the highest R&D intensity for high Life1 firms in the Dynamic and Competitive subsample. These firms are also most responsive to variation in Tobins Q (R&D shifts from 0.212 for low Q firms to 0.265 for high Q firms). In contrast, high Life3 firms in this subsample exhibit a negative Q-sensitivity (R&D shifts from 0.116 for low Q firms to 0.064 for high Q firms). Interestingly, in this subsample, firms with high Life 4 are also positively responsive to Q consistent with opportunism. The Static and Concentrated subsample exhibits very different patterns as R&D levels are low and are not responsive to Q. The highest CAPX/Assets intensity occurs for high Life2 firms in the same Dynamic and Competitive subsample. These firms are also responsive to variation in Tobins Q (CAPX shifts from 0.125 for low Q firms to 0.152 for high Q firms).

Acquisition levels are highest for high Life3 firms in the Static subsamples and Life3 firms also exhibit very high Q-sensitivities. This is consistent with our aforementioned conclusions regarding the investment pecking order shifting to inorganic investment by the time a firm matures. Asset sales are particularly high for Life4 firms, although these Life4 firms have negative Q-sensitivity. This also supports the investment pecking order as firms in decline shift to dis-investment and eventually delisting unless shocks arrive to allow these firms to escape decline via growth options allowing shifts to more youthful life cycle stages.

Although the results in Table 9 are uniformly economically important, in the interest of brevity, we leave further exploration to the reader. In conclusion, we note that the last two columns report the Q-sensitivity in each subsample to Q using the basic model used in the literature. We note that the resulting Q-sensitivities are devoid of the rich economic conclusions we were able to draw above using the life cycle conditional model. We also note that without the text based life cycle model, the four subsamples shown here would not be identified. In conclusion, the life cycle model provides first order improvements in our understanding of investment levels and Q-sensitivities. These results are backed by very large economic magnitudes and cannot be seen using models in the existing literature.

# 7 Implications for Aggregate Investment and Acquisitions

In this section, we examine if the product life cycle is related to a growing array of major changes among U.S. public firms reported in existing studies. These include declining investment, increasing explanatory power of investment-Q models, and decreasing competition.

## 7.1 Declining Investment

Figure 4 displays the average level of CAPX/assets in time series for various subsamples. The top-most figure shows results for above versus below median firm dynamism and Total Similarity. All time series averages are divided by the average value in the first year of our sample (1998). This makes the graphs more interpretable as the level of the average in each year implies the percentage growth in CAPX for the given subsample. The results in Figure 4 strongly support the conclusion in Gutierrez and Phillipon (2016) and Doidge et al. (2018): there is a strong secular decline in CAPX/assets throughout our sample period in all subsamples. However, we also find an important new result: this relative decline is much smaller for dynamic firms (24% decline during our sample) than for static firms (52% decline). In contrast, we find much less separation across subsamples based on high versus low competition.

[**Insert Figure 4 Here**]

The middle image in Figure 4 shows that these findings are even more stark for the high competition subsample. Here, CAPX only declines by 14% for dynamic firms versus 51% for static firms. These figures are more modest at 36% and 52% for the low competition subsample (lowest image). We conclude that life cycles are very important to understanding the "disappearing CAPX anomaly". In particular, the biggest declines are in static product markets having mature products, where firms lose more than half their CAPX on average. In contrast, declines are quite small for firms in dynamic product markets, particularly when competition is also high, as these firms lose just 14% of their CAPX. These differences are economically large and underscore the importance of the "rise of the dynamic firm" we noted earlier.

Figure 5 provides corresponding evidence for R&D/assets. Again, dynamic firms have higher R&D intensities than static firms. The difference is larger in competitive markets, with dynamic firms increasing their differential over static firms.[16]

[**Insert Figure 5 Here**]

[16]In the figures we split the sample annually on above and below median levels of TSIMM, our preferred measure of competition. Analogous figures using splits on the TNIC-3 and NAICS-3 Herfindahl measures of concentration, leading to the same conclusions, are shown in the Online Appendix.

## 7.2 Basic Q-investment Regressions

In this section, we follow the literature, including studies such as Gutierrez and Phillipon (2016) and Lee, Shin and Stulz (2016), and examine how the basic cross-sectional relationship between Q and corporate policies varies over our sample period, especially when we condition on the life cycle stages. We focus on explanatory power measured as the adjusted $R^2$ of these models. As above, we consider the full sample, and four subsamples based on dynamism and competitiveness. We first consider annual OLS regressions where the dependent variable is CAPX/assets, and Tobins Q is the key RHS variable controlling for firm size and age. The results are displayed in the first four columns of Table 10. Consistent with Gutierrez and Phillipon (2016), we find that the $R^2$ peaks early in our sample around 2000 at 6.9% and then sharply declines thereafter to 1.7% by the end of our sample. We then examine whether the life cycle conditional model performs differently. In particular, the conditional model replaces Tobins Q with four cross terms equal to Tobins Q multiplied by each of the life cycle variables Life1 to Life4, which sum to unity (hence the interpretation as a conditional model).

**[Insert Table 10 Here]**

The nine columns in the middle of Table 10 display the results for the conditional model. Controls for size and age are not reported to conserve space. The table shows that, unlike the basic model, where $R^2$ is low and declines, the $R^2$ for the conditional model is an order of magnitude larger and increases during our sample period. We conclude that the life cycle plays an increasingly important role over our sample. Panel A of Figure 6 illustrates these differences in explanatory power. Table 10 also shows that the level of Life2, and the sensitivity to Q for Life3 firms, are both important for predicting CAPX across firms in the cross section.

We next run the same analysis for R&D instead of CAPX in Table 11. Once again, the results are quite different between the basic and the conditional model. Both have an adjusted $R^2$ that is increasing over time, indicating the growing importance of innovation spending, but the conditional model has an adjusted $R^2$ that is roughly twice as large. Panel B in Figure 6 illustrates this increase in explanatory power over time. The coefficients in Table 11 indicate, not surprisingly, that firms in Life1 doing product innovation invest substantially more in R&D, especially when their Tobins Q is high.

**[Insert Figure 6 and Table 11 Here]**

We next run the same analysis for the propensity to be an acquirer in Table 12. Although differences in adjusted $R^2$ are less striking, the conditional model yields many insights. For example, firms with the most mature products (life3) have the highest acquisition responsiveness to Tobins' Q. This is consistent with our earlier results regarding the investment pecking order and the shift to inorganic investments as firms mature in the life cycle, and this cannot be seen using the basic model from the literature.

**[Insert Table 12 Here]**

In Table 13, we examine the propensity to sell assets. The explanatory power of the conditional model is higher. As expected, firms with high exposure to the last stage of the product cycle (life4) are heavy sellers, especially towards the end of our sample. However, these firms sharply reduce sales and increase asset purchases when their Q is high.

**[Insert Table 13 Here]**

We conclude that the relationship between Tobins' Q and investment is very rich, and basic models from the literature miss most of the inferences for various forms of investment and Q-sensitivities. Life cycles are critical to understanding these links, and to understanding why the investment-Q relationship is changing over time.

## 7.3 Explaining the Changing CAPX-Q Relationship

To better understand the relation between CAPX and Tobins Q, we plot adjusted $R^2$ over time for different model specifications and subsamples. The top graph in Figure 7 plots adjusted $R^2$ from the basic model (blue) from the literature and the conditional model that incorporates the life cycle variables (red). The explanatory power of the basic CAPX-Q regressions is generally low, and the basic model peaks early in our sample. The life cycle conditional model has much higher adjusted $R^2$ and increases over time. When we break the sample into firms with above and below median dynamism using annual breakpoints, two results emerge. First, Tobin's Q explains CAPX much better for firms with below median dynamism ("static firms", grey line), than for firms with above median dynamism (orange line). Second, when we consider static and dynamic firms separately, there is no evidence that explanatory power is declining over time. Hence the above declining trend for the basic CAPX-Q model likely arises from aggregating the two very distinct dynamic and static populations.

[**Insert Figure 7 Here**]

In the same figure in the lower two graphs, we further break the sample into above median and below median TNIC total similarity subsamples. Firms with high total similarity follow a pattern that is similar to the whole sample, albeit with significantly higher $R^2$. In contrast, there is no discernible pattern in the low total similarity subsample, and explanatory power is much lower. We conclude that the basic CAPX-Q model has the most explanatory power for static firms operating in more competitive markets. The most dynamic firms are likely following a more entrepreneurial agenda regarding CAPX, and thus are not as responsive to short term market signals.

Given the literature's focus on firm age, we control for age in all of our tests. In unreported analysis, we also note that additional controls for age-squared do not change our inferences. Because our text-based model is based on four groupings, we further consider sorting 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 8 Here]**

Figure 8 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.

# 8 Conclusion

Motivated by product life cycle classifications, we develop a text-based four-stage model of the product life cycle that aggregates to the firm-level as a vector of overall life cycle exposures. The stages are product innovation, process innovation, maturity , and decline. Theory suggests that each stage is associated with a focus on different tangible and intangible investments. We construct our life cycle model using text based analysis of firm 10-Ks, and hence we obtain firm-year observations, allowing us to examine progressions through the life cycle within-firm, and we find strong evidence of a pecking order of investment policies as firms progress through the cycle.

Our main finding is that simply conditioning the investment-Q model on the product life cycle exposures of the firm radically changes inferences regarding investment and Q. For example, existing studies generally report positive sensitivities of various investment policies to Q. We find that this relationship is first-order moderated by the life cycle, and an investment pecking order emerges. Early-stage product innovating firms focus on R&D, and further increase R&D when Q increases. Firms focused on the second stage of process innovation, in contrast, increase CAPX and acquisitions as Q increases. Mature-stage firms tend to give up on organic investment in the form of both R&D and CAPX, and focus on acquisitions. They further increase acquisitions when Q increases. These results are quite stark, and indicate that mature firms furthermore have negative sensitivity to R&D. This is novel given the literature, and it suggests that mature firms likely use R&D defensively when competitive threats or market disruptions arise. Finally, the pecking order ends with firms in decline focusing on the sale of assets (dis-investment). However, these firms reverse the life cycle and begin to acquire assets when Q increases, consistent with the possibility of product-extension for declining firms when shocks arrive.

Our results uniformly support the predictions of life cycle theories. Firms tend to drift from product innovation, to process innovation, maturity, and ultimately decline. However, this path is not deterministic. Shocks can accelerate or (more rarely) reverse this process. Negative macro-economic shocks tend to accelerate aging. However, increases in international competition and growth options tend to reverse the cycle. This latter finding likely explains why larger firms have become more dynamic and entrepreneurial during our sample period. These results suggest that the opening of international markets likely plays a supporting role in understanding the changes observed in US firms over time. Life cycle shifts are also related to the well known decline in CAPX among U.S. firms, as this decline is substantially smaller for dynamic firms than for static firms. In all, we believe that further examination of firm policies and outcomes through the lens of the product life cycles has a strong micro-foundation and can yield many novel results in both finance and economics.

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## Table 1: Summary Statistics

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

| Variable | Mean | Std. Dev. | Minimum | Median | Maximum | # Obs |
|---|---|---|---|---|---|---|
| | | | ***Panel A: Life Cycle Variables*** | | | |
| Life1 | 0.255 | 0.133 | 0.000 | 0.241 | 0.954 | 77,547 |
| Life2 | 0.395 | 0.158 | 0.016 | 0.370 | 0.992 | 77,547 |
| Life3 | 0.302 | 0.131 | 0.004 | 0.294 | 0.965 | 77,547 |
| Life4 | 0.048 | 0.064 | 0.000 | 0.027 | 0.891 | 77,547 |
| LifeDelist | 0.016 | 0.125 | 0.000 | 0.000 | 1.000 | 77,547 |
| | | | ***Panel B: Investment 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 |
| SDC Acquirer Dummy | 0.342 | 0.474 | 0.000 | 0.000 | 1.000 | 77,547 |
| SDC Target Dummy | 0.185 | 0.389 | 0.000 | 0.000 | 1.000 | 77,547 |
| Tobins Q | 1.547 | 1.812 | 0.080 | 1.035 | 34.202 | 77,547 |
| | | | ***Panel C: Real 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 | SDC Acquirer |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ***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 | | |
| SDC Acquirer | -0.036 | -0.013 | 0.060 | -0.015 | -0.071 | 0.093 | 0.294 | 0.007 | 0.125 | 0.086 | -0.098 | 0.005 | |
| SDC Target | -0.101 | 0.033 | -0.023 | 0.178 | 0.015 | 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: 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 | Adj $R^2$ | Obs. |
|---|---|---|---|---|---|---|---|
| | | ***Panel A: Firm and Year Fixed Effects*** | | | | | |
| (1) | Life1 | –0.006 | | | | 0.78 | 79,032 |
| | | (–2.08) | | | | | |
| (2) | Life2 | –0.016 | | | | 0.79 | 79,032 |
| | | (–4.97) | | | | | |
| (3) | Life3 | 0.014 | | | | 0.68 | 79,032 |
| | | (4.07) | | | | | |
| (4) | Life4 | 0.008 | | | | 0.42 | 79,032 |
| | | (4.48) | | | | | |
| (5) | LifeDelist | 0.038 | | | | 0.28 | 79,032 |
| | | (14.13) | | | | | |
| | | ***Panel B: Firm and Year Fixed Effects Plus Controls*** | | | | | |
| (6) | Life1 | –0.012 | 0.006 | 0.003 | 0.000 | 0.79 | 77,170 |
| | | (–3.67) | (5.94) | (12.46) | (–34.05) | | |
| (7) | Life2 | –0.017 | –0.002 | –0.002 | 0.000 | 0.79 | 77,170 |
| | | (–4.72) | (–1.64) | (–7.64) | (–4.68) | | |
| (8) | Life3 | 0.018 | 0.000 | 0.000 | 0.000 | 0.70 | 77,170 |
| | | (4.83) | (–0.08) | (0.49) | (30.44) | | |
| (9) | Life4 | 0.011 | –0.004 | –0.001 | 0.000 | 0.43 | 77,170 |
| | | (5.10) | (–5.13) | (–8.24) | (–5.51) | | |
| (10) | LifeDelist | 0.051 | –0.020 | –0.003 | 0.000 | 0.29 | 77,170 |
| | | (16.62) | (–12.59) | (–8.02) | (3.38) | | |

## Table 4: 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. Tobins Q is re-centered at the sample mean prior to running the regressions so that the Life1, Life2, and Life4 coefficients are interpretable as the impact of one sigma of the given variable on the dependent variable for a firm having an average Q. All specifications include firm and year fixed effects. Standard errors are clustered by firm. *t*-statistics are in parentheses.

| Row | Life1 | Life2 | 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) | 0.064 | –0.025 | –0.138 | | | | | | | –0.333 | 0.000 | | 70,793 |
| | (3.38) | (–1.54) | (–5.76) | | | | | | | (–62.34) | (3.67) | | 0.19 |
| (2) | 0.050 | –0.027 | –0.115 | | | | | –0.052 | 0.019 | –0.342 | 0.000 | 0.007 | 70,405 |
| | (2.64) | (–1.64) | (–4.81) | | | | | (–6.76) | (6.93) | (–61.78) | (2.99) | (9.27) | 0.19 |
| (3) | 0.049 | –0.028 | –0.121 | 0.009 | 0.002 | 0.008 | –0.003 | –0.052 | 0.019 | –0.342 | 0.000 | | 70,405 |
| | (2.59) | (–1.72) | (–4.87) | (3.00) | (0.70) | (1.99) | (–0.23) | (–6.76) | (6.87) | (–61.76) | (2.99) | | 0.19 |
| | | | | | | ***Panel B: Dependent Variable = Product Market Fluidity*** | | | | | | | |
| (4) | 0.910 | –0.156 | –0.068 | | | | | | | 2.267 | 0.000 | | 71,436 |
| | (5.49) | (–1.12) | (–0.34) | | | | | | | (47.73) | (4.18) | | 0.81 |
| (5) | 0.803 | –0.164 | 0.119 | | | | | –0.404 | 0.177 | 2.192 | 0.000 | 0.047 | 71,045 |
| | (4.84) | (–1.18) | (0.59) | | | | | (–5.36) | (7.36) | (45.54) | (3.41) | (8.35) | 0.82 |
| (6) | 0.770 | –0.204 | –0.038 | 0.032 | 0.000 | 0.142 | –0.242 | –0.400 | 0.173 | 2.191 | 0.000 | | 71,045 |
| | (4.65) | (–1.46) | (–0.18) | (1.36) | (0.01) | (4.39) | (–2.21) | (–5.32) | (7.21) | (45.54) | (3.35) | | 0.82 |

## Table 5: 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 tech bust shock (Panel A) or the financial crisis 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: the specified pre-treatment and post-treatment years. 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 | 0.279 | 0.005 | | –0.072 | –0.078 | –0.001 | –0.008 | 0.072 | 0.008 | 0.002 | 0.000 | 0.001 | 11,291 |
| | | (7.37) | (0.14) | | (–1.32) | (–5.44) | (–0.12) | (–0.58) | (1.54) | (0.43) | (0.52) | (1.29) | (1.42) | 0.81 |
| (2) | Life2 | –0.274 | –0.224 | | –0.321 | 0.044 | –0.032 | 0.055 | 0.058 | –0.033 | –0.002 | 0.000 | –0.001 | 11,291 |
| | | (–6.79) | | (–5.60) | (–5.11) | (2.94) | (–2.62) | (3.61) | (1.09) | (–1.70) | (–0.38) | (–0.44) | (–1.09) | 0.81 |
| (3) | Life3 | –0.216 | –0.234 | | –0.356 | 0.023 | 0.011 | –0.064 | 0.004 | 0.016 | –0.004 | 0.000 | 0.001 | 11,291 |
| | | (–5.48) | (–6.40) | | (–5.73) | (1.60) | (1.06) | (–4.18) | (0.07) | (0.82) | (–0.92) | (–0.95) | (0.55) | 0.81 |
| (4) | Life4 | –0.013 | 0.004 | | 0.525 | 0.011 | 0.021 | 0.017 | –0.134 | 0.010 | 0.004 | 0.000 | –0.001 | 11,291 |
| | | (–0.60) | (0.20) | | (8.59) | (1.31) | (3.46) | (1.92) | (–2.39) | (0.91) | (1.20) | (0.50) | (–1.10) | 0.73 |
| (5) | LifeDelist | –0.065 | –0.017 | | 0.077 | 0.061 | 0.033 | 0.002 | 0.112 | 0.123 | –0.048 | 0.000 | –0.004 | 11,291 |
| | | (–0.99) | (–0.28) | | (0.65) | (1.81) | (1.48) | (0.08) | (1.02) | (3.35) | (–3.63) | (0.49) | (–1.59) | 0.50 |
| ***Panel B: Shock is comparison of 2009 to 2007 (financial crisis shock)*** | | | | | | | | | | | | | | |
| (6) | Life1 | 0.271 | –0.029 | | –0.068 | –0.051 | –0.004 | 0.013 | 0.040 | 0.022 | 0.002 | 0.000 | 0.000 | 7,985 |
| | | (7.04) | (–1.10) | | (–1.94) | (–4.01) | (–0.66) | (1.22) | (1.65) | (1.33) | (0.61) | (0.17) | (–0.29) | 0.90 |
| (7) | Life2 | –0.297 | –0.254 | | –0.361 | 0.004 | –0.006 | –0.009 | 0.118 | –0.025 | 0.000 | 0.000 | –0.001 | 7,985 |
| | | (–6.55) | | (–6.10) | (–6.03) | (0.28) | (–0.67) | (–0.73) | (2.95) | (–1.23) | (0.05) | (–0.13) | (–0.50) | 0.89 |
| (8) | Life3 | –0.238 | –0.249 | | –0.345 | 0.029 | –0.001 | –0.010 | 0.075 | –0.001 | 0.003 | 0.000 | 0.002 | 7,985 |
| | | (–5.38) | (–6.39) | | (–7.22) | (2.08) | (–0.13) | (–0.69) | (2.46) | (–0.04) | (0.55) | (–1.47) | (1.37) | 0.84 |
| (9) | Life4 | 0.010 | 0.024 | | 0.520 | 0.018 | 0.011 | 0.006 | –0.233 | 0.004 | –0.006 | 0.000 | –0.001 | 7,985 |
| | | (0.43) | (0.85) | | (10.49) | (2.18) | (1.96) | (0.79) | (–6.57) | (0.29) | (–1.31) | (2.23) | (–1.21) | 0.74 |
| (10) | LifeDelist | –0.012 | –0.006 | | –0.073 | 0.021 | 0.013 | –0.003 | 0.058 | 0.057 | –0.019 | 0.000 | –0.005 | 7,985 |
| | | (–0.14) | (–0.09) | | (–0.77) | (0.74) | (0.85) | (–0.12) | (0.81) | (1.52) | (–1.33) | (1.43) | (–0.88) | 0.50 |

## Table 6: 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 | $R^2$ | Obs |
|---|---|---|---|---|---|---|---|---|---|
| | | | | ***Panel A: Text-Based International Competition Shock*** | | | | | |
| (1) | Life1 | 0.007 | | –0.011 | 0.004 | 0.003 | 0.000 | 0.78 | 77,170 |
| | | (5.32) | | (–3.49) | (3.70) | (11.89) | (–7.79) | | |
| (2) | Life1 | | 0.030 | –0.013 | 0.004 | 0.003 | 0.000 | 0.78 | 76,058 |
| | | | (5.17) | (–3.81) | (3.65) | (11.59) | (–7.68) | | |
| (3) | Life2 | 0.001 | | –0.018 | –0.002 | –0.002 | 0.000 | 0.79 | 77,170 |
| | | (0.61) | | (–4.78) | (–1.60) | (–7.73) | (–5.41) | | |
| (4) | Life2 | | –0.017 | –0.017 | –0.002 | –0.002 | 0.000 | 0.79 | 76,058 |
| | | | (–2.41) | (–4.63) | (–1.47) | (–7.28) | (–5.51) | | |
| (5) | Life3 | –0.010 | | 0.017 | 0.003 | 0.000 | 0.000 | 0.68 | 77,170 |
| | | (–6.31) | | (4.56) | (2.38) | (0.93) | (7.05) | | |
| (6) | Life3 | | –0.014 | 0.018 | 0.003 | 0.000 | 0.000 | 0.68 | 76,058 |
| | | | (–1.99) | (4.68) | (2.20) | (0.82) | (6.98) | | |
| (7) | Life4 | 0.002 | | 0.012 | –0.005 | –0.001 | 0.000 | 0.43 | 77,170 |
| | | (1.79) | | (5.30) | (–6.06) | (–8.28) | (6.05) | | |
| (8) | Life4 | | 0.001 | 0.012 | –0.005 | –0.001 | 0.000 | 0.43 | 76,058 |
| | | | (0.21) | (5.09) | (–5.81) | (–8.14) | (6.09) | | |
| | | | | ***Panel B: Text-Based International Growth Opportunity Shock*** | | | | | |
| (9) | Life1 | 0.008 | | –0.011 | 0.004 | 0.003 | 0.000 | 0.78 | 77,170 |
| | | (6.48) | | (–3.57) | (3.63) | (11.74) | (–8.15) | | |
| (10) | Life1 | | 0.055 | –0.012 | 0.003 | 0.003 | 0.000 | 0.78 | 76,058 |
| | | | (9.84) | (–3.70) | (3.27) | (11.13) | (–8.13) | | |
| (11) | Life2 | –0.005 | | –0.018 | –0.002 | –0.002 | 0.000 | 0.79 | 77,170 |
| | | (–3.48) | | (–4.79) | (–1.40) | (–7.67) | (–5.22) | | |
| (12) | Life2 | | –0.040 | –0.018 | –0.001 | –0.002 | 0.000 | 0.79 | 76,058 |
| | | | (–6.43) | (–4.75) | (–1.23) | (–6.86) | (–5.29) | | |
| (13) | Life3 | –0.002 | | 0.017 | 0.003 | 0.000 | 0.000 | 0.68 | 77,170 |
| | | (–1.67) | | (4.64) | (2.16) | (1.03) | (7.09) | | |
| (14) | Life3 | | 0.001 | 0.018 | 0.003 | 0.000 | 0.000 | 0.68 | 76,058 |
| | | | (0.16) | (4.73) | (2.22) | (0.77) | (7.00) | | |
| (15) | Life4 | –0.001 | | 0.011 | –0.005 | –0.001 | 0.000 | 0.43 | 77,170 |
| | | (–0.69) | | (5.28) | (–5.94) | (–8.27) | (6.07) | | |
| (16) | Life4 | | –0.016 | 0.011 | –0.004 | –0.001 | 0.000 | 0.43 | 76,058 |
| | | | (–3.53) | (4.99) | (–5.67) | (–7.86) | (6.19) | | |

# Table 7: Investment Panel Data Regressions

The table reports results from firm-year panel data investment-Q regressions from 1998 to 2015. The dependent variable is ex post R&D/assets (Panels A) or CAPX/Assets (Panel B). In each panel, we examine the overall sample, subsamples with above and below median competition, above and below median dynamism, and above and below median firm age. Competition is measured using TNIC-3 total similarity from Hoberg and Phillips (2016) (results are similar if we instead use a NAICS-based HHI, see online appendix). All RHS variables are ex ante measurable and are observable in year $t-1$. In all models, the dependent variable is regressed on ex-ante life cycle variables, interactions with Tobins Q, and size plus age controls. Tobins Q is re-centered at the sample mean prior to running the regressions so that the Life1, Life2, and Life4 coefficients are interpretable as the impact of one sigma of the given variable on the dependent variable for a firm having an average Q. 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 | Sample | 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*** | | | | | | | | |
| (1) | Overall | 0.007 | -0.025 | 0.006 | 0.037 | 0.005 | -0.008 | 0.025 | -0.001 | -0.009 | 0.010 | -0.025 | 0.006 | 0.83 | 76,135 |
| | | (14.83) | (-19.75) | (2.87) | (6.89) | (1.30) | (-1.21) | (11.34) | (-0.88) | (-3.81) | (1.25) | (-20.29) | (3.07) | | |
| (2) | High Comp. | 0.008 | -0.038 | 0.007 | 0.053 | 0.009 | -0.001 | 0.027 | 0.000 | -0.011 | 0.017 | -0.038 | 0.007 | 0.84 | 37,901 |
| | | (13.40) | (-17.53) | (2.13) | (6.03) | (1.51) | (-0.07) | (9.83) | (-0.11) | (-3.26) | (1.20) | (-17.97) | (2.25) | | |
| (3) | Low Comp. | 0.004 | -0.014 | 0.005 | 0.016 | 0.000 | -0.008 | 0.012 | 0.000 | -0.002 | 0.008 | -0.014 | 0.005 | 0.81 | 37,911 |
| | | (5.07) | (-10.50) | (2.04) | (3.12) | (-0.12) | (-1.44) | (3.05) | (0.18) | (-0.97) | (0.96) | (-10.62) | (2.18) | | |
| (4) | Dynamic | 0.008 | -0.034 | 0.001 | 0.042 | 0.011 | -0.004 | 0.030 | 0.000 | -0.024 | 0.011 | -0.035 | 0.001 | 0.82 | 38,079 |
| | | (11.15) | (-15.96) | (0.20) | (3.50) | (1.23) | (-0.33) | (9.00) | (0.05) | (-3.84) | (1.03) | (-16.53) | (0.21) | | |
| (5) | Static | 0.005 | -0.016 | 0.008 | 0.020 | -0.007 | -0.007 | 0.016 | -0.007 | 0.003 | 0.009 | -0.016 | 0.008 | 0.85 | 38,056 |
| | | (8.06) | (-12.04) | (4.41) | (2.81) | (-1.32) | (-0.65) | (4.95) | (-2.12) | (0.90) | (0.78) | (-12.37) | (4.57) | | |
| (6) | Old Firms | 0.007 | -0.019 | -0.001 | 0.033 | 0.001 | -0.009 | 0.025 | 0.000 | -0.008 | -0.002 | -0.019 | 0.003 | 0.83 | 38,204 |
| | | (8.10) | (-11.13) | (-0.12) | (5.89) | (0.29) | (-1.35) | (7.24) | (-0.21) | (-2.39) | (-0.28) | (-11.50) | (0.48) | | |
| (7) | Young Firms | 0.007 | -0.031 | 0.034 | 0.036 | 0.009 | -0.017 | 0.024 | -0.001 | -0.010 | 0.026 | -0.031 | 0.032 | 0.83 | 37,931 |
| | | (11.90) | (-16.31) | (6.25) | (3.84) | (1.35) | (-1.42) | (8.27) | (-0.57) | (-2.89) | (1.72) | (-16.66) | (5.96) | | |
| | | | | | | | ***Panel B: CAPX/Assets Issuance*** | | | | | | | | |
| (8) | Overall | 0.007 | -0.011 | -0.011 | 0.017 | -0.001 | -0.031 | -0.002 | 0.017 | 0.008 | 0.011 | -0.011 | -0.010 | 0.62 | 76,135 |
| | | (22.11) | (-14.34) | (-5.51) | (3.91) | (-0.30) | (-5.40) | (-1.37) | (6.01) | (4.28) | (2.07) | (-14.39) | (-5.33) | | |
| (9) | High Comp. | 0.007 | -0.010 | -0.010 | 0.017 | 0.003 | -0.027 | -0.002 | 0.017 | 0.009 | 0.015 | -0.010 | -0.010 | 0.68 | 37,901 |
| | | (17.02) | (-8.49) | (-3.62) | (3.03) | (0.47) | (-2.75) | (-1.19) | (4.14) | (3.66) | (1.58) | (-8.42) | (-3.55) | | |
| (10) | Low Comp. | 0.008 | -0.013 | -0.015 | 0.015 | -0.010 | -0.033 | -0.001 | 0.017 | 0.007 | 0.008 | -0.013 | -0.015 | 0.53 | 37,911 |
| | | (12.85) | (-12.30) | (-4.78) | (2.19) | (-1.85) | (-4.53) | (-0.20) | (3.91) | (2.16) | (1.17) | (-12.67) | (-4.63) | | |
| (11) | Dynamic | 0.007 | -0.011 | -0.023 | 0.023 | -0.001 | -0.028 | -0.003 | 0.016 | 0.011 | 0.017 | -0.011 | -0.022 | 0.60 | 38,079 |
| | | (15.56) | (-9.05) | (-6.43) | (2.26) | (-0.09) | (-2.59) | (-1.55) | (4.25) | (1.96) | (2.45) | (-9.05) | (-6.15) | | |
| (12) | Static | 0.007 | -0.011 | -0.002 | 0.009 | -0.005 | -0.029 | -0.004 | 0.013 | 0.012 | 0.001 | -0.011 | -0.002 | 0.64 | 38,056 |
| | | (12.92) | (-11.81) | (-0.96) | (1.27) | (-0.80) | (-2.74) | (-1.46) | (4.34) | (3.73) | (0.12) | (-11.75) | (-0.96) | | |
| (13) | Old Firms | 0.007 | -0.009 | -0.003 | 0.014 | -0.003 | -0.023 | 0.000 | 0.012 | 0.011 | 0.013 | -0.009 | -0.004 | 0.62 | 38,204 |
| | | (12.86) | (-8.25) | (-0.54) | (2.63) | (-0.55) | (-3.32) | (0.04) | (3.40) | (3.90) | (1.90) | (-8.56) | (-0.73) | | |
| (14) | Young Firms | 0.007 | -0.013 | -0.011 | 0.020 | -0.006 | -0.045 | -0.005 | 0.024 | 0.006 | 0.009 | -0.013 | -0.010 | 0.63 | 37,931 |
| | | (17.18) | (-11.90) | (-2.46) | (3.05) | (-0.88) | (-4.55) | (-2.65) | (8.45) | (2.47) | (1.06) | (-11.87) | (-2.14) | | |

# Table 8: Restructuring Panel Data Regressions

The table reports results from firm-year panel data OLS investment-Q regressions from 1998 to 2015. The dependent variable is the ex post acquisition dummy (Panel A), or the ex post target dummy (Panel B) in year $t$. The acquisition dummy is one if the firm acquires any assets in the given year according to SDC Platinum. The target dummy is one if the firm sells any assets in the given year according to SDC Platinum. In each panel, we examine the overall sample, subsamples with above and below median competition, above and below median dynamism, and above and below median firm age. Competition is measured using TNIC-3 total similarity from Hoberg and Phillips (2016) (results are similar if we instead use a NAICS-based HHI, see online appendix). All RHS variables are ex ante measurable and are observable in year $t-1$. In all models, the dependent variable is regressed on ex-ante life cycle variables, interactions with Tobins Q, and size plus age controls. Tobins Q is re-centered at the sample mean prior to running the regressions so that the Life1, Life2, and Life4 coefficients are interpretable as the impact of one sigma of the given variable on the dependent variable for a firm having an average Q. 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 | Sample | 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: SDC Acquisition Dummy*** | | | | | | | |
| (1) | Overall | 0.016 | 0.015 | -0.052 | 0.030 | -0.033 | -0.259 | -0.024 | 0.031 | 0.048 | 0.069 | 0.012 | -0.048 | 0.27 | 76,135 |
| | | (12.26) | (3.22) | (-3.79) | (0.89) | (-1.09) | (-5.72) | (-4.47) | (4.57) | (6.49) | (3.09) | (2.62) | (-3.56) | | |
| (2) | High Comp. | 0.011 | 0.015 | -0.037 | -0.003 | -0.002 | -0.306 | -0.019 | 0.017 | 0.042 | 0.092 | 0.012 | -0.035 | 0.28 | 37,901 |
| | | (7.20) | (2.14) | (-1.91) | (-0.07) | (-0.05) | (-4.05) | (-2.96) | (2.10) | (4.69) | (2.43) | (1.83) | (-1.82) | | |
| (3) | Low Comp. | 0.025 | 0.014 | -0.044 | 0.044 | -0.049 | -0.177 | -0.023 | 0.047 | 0.049 | 0.046 | 0.011 | -0.040 | 0.27 | 37,911 |
| | | (9.07) | (2.01) | (-2.05) | (0.85) | (-1.14) | (-2.96) | (-2.02) | (4.50) | (3.60) | (1.55) | (1.65) | (-1.89) | | |
| (4) | Dynamic | 0.014 | 0.010 | -0.036 | -0.021 | -0.027 | -0.274 | -0.029 | 0.020 | 0.079 | 0.074 | 0.008 | -0.029 | 0.26 | 38,079 |
| | | (7.43) | (1.52) | (-1.73) | (-0.32) | (-0.45) | (-3.75) | (-3.98) | (2.71) | (4.53) | (2.75) | (1.19) | (-1.40) | | |
| (5) | Static | 0.019 | 0.016 | -0.047 | 0.116 | -0.014 | -0.213 | -0.020 | 0.056 | 0.028 | 0.039 | 0.014 | -0.046 | 0.29 | 38,056 |
| | | (8.24) | (2.19) | (-2.33) | (1.99) | (-0.25) | (-2.41) | (-1.48) | (3.14) | (1.75) | (0.76) | (1.87) | (-2.27) | | |
| (6) | Old Firms | 0.019 | 0.014 | 0.073 | 0.040 | -0.018 | -0.202 | -0.029 | 0.021 | 0.071 | 0.101 | 0.011 | 0.070 | 0.29 | 38,204 |
| | | (7.89) | (1.85) | (1.52) | (0.84) | (-0.45) | (-3.48) | (-3.70) | (2.50) | (5.67) | (3.80) | (1.43) | (1.46) | | |
| (7) | Young Firms | 0.014 | 0.010 | -0.124 | 0.069 | -0.044 | -0.314 | -0.017 | 0.040 | 0.033 | 0.001 | 0.007 | -0.118 | 0.27 | 37,931 |
| | | (8.91) | (1.64) | (-4.08) | (1.39) | (-0.95) | (-4.10) | (-2.38) | (4.46) | (3.43) | (0.03) | (1.19) | (-3.93) | | |
| | | | | | | | | ***Panel B: SDC Target Dummy*** | | | | | | | |
| (8) | Overall | -0.005 | 0.038 | 0.045 | -0.026 | -0.030 | 0.078 | 0.005 | -0.009 | -0.006 | -0.085 | 0.039 | 0.044 | 0.21 | 76,135 |
| | | (-4.97) | (10.44) | (4.22) | (-0.97) | (-1.22) | (2.02) | (1.39) | (-2.19) | (-1.09) | (-4.74) | (10.59) | (4.10) | | |
| (9) | High Comp. | -0.003 | 0.042 | 0.036 | -0.035 | -0.024 | 0.113 | 0.002 | -0.004 | -0.005 | -0.053 | 0.043 | 0.035 | 0.23 | 37,901 |
| | | (-2.60) | (7.94) | (2.38) | (-0.92) | (-0.70) | (1.80) | (0.44) | (-0.91) | (-0.69) | (-1.80) | (8.02) | (2.33) | | |
| (10) | Low Comp. | -0.008 | 0.033 | 0.053 | -0.040 | -0.038 | 0.032 | 0.006 | -0.014 | -0.003 | -0.101 | 0.033 | 0.053 | 0.20 | 37,911 |
| | | (-4.01) | (6.00) | (3.09) | (-0.95) | (-1.04) | (0.61) | (0.78) | (-1.78) | (-0.33) | (-3.70) | (6.13) | (3.04) | | |
| (11) | Dynamic | -0.004 | 0.040 | 0.055 | 0.023 | -0.005 | 0.113 | 0.004 | -0.003 | -0.004 | -0.103 | 0.040 | 0.054 | 0.21 | 38,079 |
| | | (-2.95) | (7.48) | (3.25) | (0.41) | (-0.10) | (1.72) | (0.83) | (-0.75) | (-0.32) | (-3.86) | (7.58) | (3.15) | | |
| (12) | Static | -0.006 | 0.039 | 0.040 | -0.076 | -0.044 | -0.033 | 0.005 | -0.037 | 0.005 | -0.048 | 0.039 | 0.040 | 0.23 | 38,056 |
| | | (-3.54) | (6.59) | (2.58) | (-1.66) | (-1.02) | (-0.43) | (0.53) | (-2.88) | (0.40) | (-1.14) | (6.52) | (2.55) | | |
| (13) | Old Firms | -0.007 | 0.049 | 0.098 | -0.045 | -0.060 | 0.036 | 0.004 | -0.009 | -0.009 | -0.067 | 0.049 | 0.096 | 0.24 | 38,204 |
| | | (-3.80) | (8.12) | (2.41) | (-1.14) | (-1.72) | (0.71) | (0.68) | (-1.84) | (-1.03) | (-2.98) | (8.16) | (2.36) | | |
| (14) | Young Firms | -0.004 | 0.027 | 0.054 | -0.006 | 0.021 | 0.130 | 0.008 | -0.007 | -0.008 | -0.116 | 0.028 | 0.052 | 0.16 | 37,931 |
| | | (-3.30) | (5.35) | (2.41) | (-0.15) | (0.59) | (1.98) | (1.49) | (-0.91) | (-1.05) | (-3.93) | (5.49) | (2.33) | | |

## Table 9: Economic Magnitudes

The table reports economic magnitudes of the relationship between our life cycle variables and investment policies, and the sensitivity of these policies to Tobins Q. In both panels, the first three columns report the investment policy being analyzed, the subsample considered, and the average value of the dependent variable in each subsample. In the later columns, we then consider the average value of the dependent variable based on further subsamples formed by sorting on the life cycle variables and Tobin's Q. In Panel A, the last four columns report the average value of the dependent variable in the highest quartile of the given life cycle variable minus the average value for the lowest quartile. Hence these are inter-quartile ranges of the investment policies. In Panel B, we report Q-sensitivities in the last five columns. In the first four of the last five columns, we first sort firms into quartiles based on the denoted life cycle variable and we only retain the highest quartile firms. In the last column, we include all firms. For all five columns, we then sort firms into quartiles based on Tobin's Q, and compute the difference in the mean value of the dependent variable in the highest Q subsample less that of the lowest Q subsample. Hence these are inter-quartile ranges of the investment policies that specifically indicate the sensitivity of each investment policy to Tobin's Q, specifically for firms highly exposed to each life cycle stage or unconditionally. All sorts are performed annually.

| Row | Dependent Variable | Subsample | Mean Dep. Var | High Life1 Firms | High Life2 Firms | High Life3 Firms | High Life4 Firms | All Firms |
|---|---|---|---|---|---|---|---|---|
| | | | | Panel A: Investment Levels and Life Cycle Variables | | | | |
| 1 | R&D/Assets | Full Sample | 0.047 | 0.130 | -0.083 | -0.060 | 0.024 | |
| 2 | CAPX/Assets | Full Sample | 0.051 | -0.026 | 0.048 | -0.040 | -0.009 | |
| 3 | SDC Acq | Full Sample | 0.344 | -0.033 | -0.010 | 0.085 | 0.027 | |
| 4 | SDC Target | Full Sample | 0.187 | -0.082 | 0.039 | 0.000 | 0.108 | |
| | | | | Panel B: Investment Q-Sensitivities and Life Cycle Variables | | | | |
| 1 | R&D/Assets | Full Sample | 0.047 | 0.178 | 0.009 | 0.049 | 0.085 | 0.105 |
| 2 | CAPX/Assets | Full Sample | 0.051 | 0.035 | 0.079 | 0.060 | 0.035 | 0.051 |
| 3 | SDC Acq | Full Sample | 0.344 | 0.065 | 0.129 | 0.239 | 0.095 | 0.117 |
| 4 | SDC Target | Full Sample | 0.187 | -0.042 | -0.036 | 0.030 | -0.083 | -0.037 |
| | | | | Panel C: Dynamism and Competition Subsamples | | | | |
| 1 | R&D/Assets | Dyn & Compet | 0.101 | 0.250 | 0.002 | 0.128 | 0.150 | 0.182 |
| 2 | R&D/Assets | Static & Compet | 0.032 | 0.152 | 0.015 | 0.038 | 0.114 | 0.105 |
| 3 | R&D/Assets | Dyn & Concen | 0.033 | 0.087 | 0.002 | 0.035 | 0.037 | 0.050 |
| 4 | R&D/Assets | Static & Concen | 0.024 | 0.055 | 0.005 | 0.023 | 0.030 | 0.032 |
| 5 | CAPX/Assets | Dyn & Compet | 0.071 | 0.029 | 0.122 | 0.060 | 0.033 | 0.047 |
| 6 | CAPX/Assets | Static & Compet | 0.031 | 0.056 | 0.082 | 0.072 | 0.047 | 0.062 |
| 7 | CAPX/Assets | Dyn & Concen | 0.055 | 0.031 | 0.046 | 0.041 | 0.028 | 0.035 |
| 8 | CAPX/Assets | Static & Concen | 0.048 | 0.026 | 0.033 | 0.037 | 0.026 | 0.032 |
| 9 | SDC Acq | Dyn & Compet | 0.293 | -0.023 | 0.068 | 0.145 | 0.034 | 0.038 |
| 10 | SDC Acq | Static & Compet | 0.348 | 0.214 | 0.173 | 0.274 | 0.130 | 0.188 |
| 11 | SDC Acq | Dyn & Concen | 0.334 | 0.054 | 0.158 | 0.238 | 0.156 | 0.142 |
| 12 | SDC Acq | Static & Concen | 0.401 | 0.148 | 0.200 | 0.239 | 0.147 | 0.204 |
| 13 | SDC Target | Dyn & Compet | 0.177 | -0.026 | -0.035 | 0.033 | -0.139 | -0.072 |
| 14 | SDC Target | Static & Compet | 0.180 | -0.006 | 0.023 | 0.088 | -0.043 | 0.008 |
| 15 | SDC Target | Dyn & Concen | 0.199 | -0.045 | -0.041 | 0.002 | -0.067 | -0.064 |
| 16 | SDC Target | Static & Concen | 0.193 | -0.013 | -0.069 | -0.046 | -0.045 | -0.049 |

## Table 10: CAPX Investment-Q Regressions

The table reports 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 observable in year $t-1$. In all, the results below are based on two distinct Q-models. The first block of four columns is the basic investment-Q regression where CAPX/assets is regressed on ex-ante Tobins Q and 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). $t$-statistics are in parentheses.

| | Basic Model | | | | Conditional Model | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 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 $R^2$ |
| (1) 1998 | 0.009 | -0.007 | 0.001 | 0.024 | 0.003 | 0.155 | N/A | -0.058 | -0.013 | 0.013 | 0.044 | -0.023 | 0.103 |
| | (11.0) | (-3.48) | (0.75) | | (0.24) | (15.2) | | (-2.41) | (-3.71) | (3.97) | (9.51) | (-1.36) | |
| (2) 1999 | 0.007 | 0.001 | -0.001 | 0.035 | 0.013 | 0.106 | N/A | -0.071 | -0.003 | -0.004 | 0.037 | -0.002 | 0.103 |
| | (13.9) | (0.84) | (-1.19) | | (1.42) | (13.4) | | (-3.64) | (-1.28) | (-2.14) | (13.0) | (-0.14) | |
| (3) 2000 | 0.006 | 0.004 | -0.003 | 0.069 | 0.023 | 0.115 | N/A | -0.048 | -0.002 | 0.002 | 0.019 | 0.017 | 0.120 |
| | (19.0) | (2.28) | (-4.07) | | (2.06) | (12.2) | | (-2.13) | (-1.08) | (1.41) | (10.6) | (2.59) | |
| (4) 2001 | 0.005 | 0.007 | -0.001 | 0.038 | 0.021 | 0.127 | N/A | -0.031 | -0.003 | 0.008 | 0.017 | -0.015 | 0.125 |
| | (14.0) | (5.27) | (-1.34) | | (2.45) | (17.9) | | (-1.92) | (-1.81) | (5.38) | (8.44) | (-1.76) | |
| (5) 2002 | 0.006 | 0.007 | -0.001 | 0.046 | 0.012 | 0.098 | N/A | -0.006 | -0.002 | 0.002 | 0.023 | 0.021 | 0.134 |
| | (14.1) | (6.88) | (-1.65) | | (1.69) | (16.8) | | (-0.50) | (-1.04) | (0.98) | (9.74) | (2.37) | |
| (6) 2003 | 0.009 | 0.007 | -0.000 | 0.049 | 0.031 | 0.130 | N/A | -0.008 | 0.007 | 0.003 | 0.019 | 0.011 | 0.153 |
| | (14.2) | (5.46) | (-1.16) | | (3.91) | (20.3) | | (-0.63) | (2.61) | (1.69) | (5.76) | (1.04) | |
| (7) 2004 | 0.007 | 0.006 | -0.001 | 0.038 | 0.006 | 0.142 | N/A | 0.001 | -0.000 | 0.000 | 0.024 | 0.024 | 0.160 |
| | (11.4) | (3.88) | (-2.88) | | (0.63) | (19.2) | | (0.08) | (-0.00) | (0.20) | (7.88) | (2.32) | |
| (8) 2005 | 0.006 | 0.006 | -0.001 | 0.024 | 0.020 | 0.181 | N/A | -0.004 | -0.006 | 0.003 | 0.021 | 0.025 | 0.176 |
| | (8.71) | (3.65) | (-1.84) | | (1.94) | (21.4) | | (-0.27) | (-2.09) | (1.64) | (6.63) | (2.19) | |
| (9) 2006 | 0.009 | 0.003 | 0.000 | 0.028 | 0.012 | 0.209 | N/A | 0.010 | -0.006 | 0.012 | 0.021 | 0.041 | 0.193 |
| | (10.3) | (1.73) | (0.26) | | (0.98) | (21.6) | | (0.50) | (-1.67) | (4.37) | (4.98) | (2.63) | |
| (10) 2007 | 0.007 | -0.004 | 0.002 | 0.019 | 0.009 | 0.238 | N/A | 0.030 | 0.009 | -0.004 | 0.019 | 0.033 | 0.202 |
| | (8.77) | (-1.97) | (2.80) | | (0.66) | (23.3) | | (1.47) | (2.60) | (-1.64) | (5.11) | (2.08) | |
| (11) 2008 | 0.007 | -0.004 | 0.002 | 0.023 | 0.016 | 0.237 | N/A | 0.016 | -0.004 | 0.001 | 0.023 | 0.055 | 0.220 |
| | (9.51) | (-2.11) | (3.42) | | (1.22) | (24.2) | | (0.82) | (-1.15) | (0.49) | (6.15) | (3.53) | |
| (12) 2009 | 0.008 | 0.000 | 0.002 | 0.030 | 0.009 | 0.121 | N/A | 0.012 | -0.005 | 0.000 | 0.028 | 0.047 | 0.189 |
| | (10.8) | (0.31) | (4.07) | | (1.17) | (20.8) | | (1.04) | (-1.46) | (0.00) | (7.77) | (3.31) | |
| (13) 2010 | 0.009 | -0.004 | 0.002 | 0.030 | 0.018 | 0.163 | N/A | 0.004 | -0.010 | 0.010 | 0.025 | 0.022 | 0.196 |
| | (10.3) | (-2.58) | (3.37) | | (1.71) | (20.7) | | (0.27) | (-2.97) | (4.06) | (6.61) | (1.43) | |
| (14) 2011 | 0.009 | -0.003 | 0.002 | 0.027 | 0.015 | 0.197 | N/A | 0.008 | -0.005 | 0.006 | 0.026 | 0.017 | 0.207 |
| | (9.69) | (-1.59) | (3.19) | | (1.26) | (21.2) | | (0.41) | (-1.34) | (1.92) | (5.93) | (0.93) | |
| (15) 2012 | 0.009 | -0.007 | 0.002 | 0.025 | 0.011 | 0.218 | N/A | 0.012 | -0.011 | 0.003 | 0.036 | 0.030 | 0.231 |
| | (8.59) | (-3.66) | (3.00) | | (0.80) | (21.9) | | (0.51) | (-2.54) | (0.98) | (7.24) | (1.25) | |
| (16) 2013 | 0.007 | -0.004 | 0.002 | 0.025 | -0.005 | 0.179 | N/A | 0.029 | -0.001 | -0.003 | 0.031 | 0.021 | 0.224 |
| | (8.71) | (-2.27) | (2.69) | | (-0.42) | (20.8) | | (1.44) | (-0.25) | (-1.63) | (8.26) | (1.20) | |
| (17) 2014 | 0.006 | -0.007 | 0.002 | 0.021 | -0.013 | 0.216 | N/A | 0.013 | 0.002 | 0.000 | 0.026 | -0.003 | 0.216 |
| | (7.18) | (-3.56) | (3.00) | | (-0.94) | (20.5) | | (0.56) | (0.61) | (0.00) | (6.22) | (-0.14) | |
| (18) 2015 | 0.004 | -0.004 | 0.002 | 0.017 | -0.015 | 0.138 | N/A | 0.031 | -0.001 | -0.002 | 0.021 | 0.026 | 0.182 |
| | (6.65) | (-2.89) | (3.36) | | (-1.47) | (17.3) | | (1.72) | (-0.47) | (-0.97) | (7.35) | (1.80) | |

# Table 11: R&D Investment-Q Regressions

The table reports 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 observable in year $t-1$. In all, the results below are based on two models. The first block of four columns is the basic investment-Q regression where R&D/assets is regressed on ex-ante Tobins Q and 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). $t$-statistics are in parentheses.

| | Basic Model | | | | Conditional Model | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 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 $R^2$ |
| (1) 1998 | 0.025 | -0.006 | -0.009 | 0.212 | 0.312 | 0.025 | N/A | 0.136 | 0.071 | -0.004 | -0.028 | 0.056 | 0.400 |
| | (31.4) | (-3.19) | (-13.7) | | (30.4) | (2.87) | | (6.67) | (24.1) | (-1.46) | (-7.29) | (3.93) | |
| (2) 1999 | 0.023 | -0.005 | -0.012 | 0.228 | 0.346 | 0.025 | N/A | 0.164 | 0.070 | -0.004 | -0.034 | 0.068 | 0.418 |
| | (31.8) | (-2.38) | (-16.8) | | (30.1) | (2.57) | | (6.82) | (25.5) | (-1.44) | (-9.65) | (4.23) | |
| (3) 2000 | 0.014 | 0.002 | -0.015 | 0.265 | 0.369 | 0.045 | N/A | 0.168 | 0.035 | 0.002 | -0.017 | 0.036 | 0.408 |
| | (35.7) | (0.90) | (-19.2) | | (28.2) | (4.06) | | (6.40) | (20.5) | (1.19) | (-7.92) | (4.59) | |
| (4) 2001 | 0.016 | -0.007 | -0.011 | 0.270 | 0.290 | 0.026 | N/A | 0.116 | 0.033 | 0.003 | -0.013 | 0.029 | 0.436 |
| | (35.7) | (-4.67) | (-18.1) | | (30.1) | (3.23) | | (6.36) | (19.9) | (1.52) | (-5.54) | (3.12) | |
| (5) 2002 | 0.022 | -0.009 | -0.010 | 0.268 | 0.275 | 0.027 | N/A | 0.140 | 0.054 | 0.002 | -0.027 | 0.071 | 0.458 |
| | (33.1) | (-5.37) | (-17.2) | | (28.3) | (3.35) | | (8.30) | (21.9) | (0.75) | (-8.19) | (5.71) | |
| (6) 2003 | 0.023 | -0.012 | -0.011 | 0.206 | 0.337 | 0.033 | N/A | 0.110 | 0.085 | -0.004 | -0.041 | 0.043 | 0.458 |
| | (23.0) | (-6.41) | (-17.0) | | (31.2) | (3.75) | | (6.59) | (23.0) | (-1.66) | (-9.06) | (2.81) | |
| (7) 2004 | 0.021 | -0.008 | -0.009 | 0.232 | 0.338 | 0.043 | N/A | 0.090 | 0.072 | -0.001 | -0.032 | -0.009 | 0.461 |
| | (25.7) | (-4.05) | (-14.0) | | (30.4) | (4.83) | | (5.26) | (23.0) | (-0.63) | (-8.71) | (-0.71) | |
| (8) 2005 | 0.017 | -0.009 | -0.009 | 0.209 | 0.359 | 0.050 | N/A | 0.075 | 0.072 | -0.008 | -0.025 | -0.016 | 0.490 |
| | (21.9) | (-4.53) | (-12.9) | | (31.8) | (5.51) | | (4.32) | (23.9) | (-3.96) | (-7.27) | (-1.32) | |
| (9) 2006 | 0.023 | -0.008 | -0.011 | 0.215 | 0.405 | 0.065 | N/A | 0.084 | 0.094 | -0.011 | -0.035 | -0.047 | 0.504 |
| | (22.4) | (-3.85) | (-13.8) | | (31.7) | (6.61) | | (4.27) | (24.3) | (-4.00) | (-8.24) | (-2.95) | |
| (10) 2007 | 0.020 | -0.006 | -0.012 | 0.192 | 0.447 | 0.082 | N/A | 0.104 | 0.091 | -0.011 | -0.036 | -0.028 | 0.503 |
| | (20.1) | (-2.78) | (-13.8) | | (32.4) | (7.67) | | (4.88) | (25.6) | (-4.86) | (-9.13) | (-1.64) | |
| (11) 2008 | 0.017 | -0.004 | -0.012 | 0.186 | 0.424 | 0.071 | N/A | 0.111 | 0.077 | -0.008 | -0.030 | -0.021 | 0.495 |
| | (19.5) | (-1.93) | (-15.1) | | (33.8) | (7.30) | | (5.74) | (23.1) | (-4.13) | (-7.95) | (-1.35) | |
| (12) 2009 | 0.026 | -0.005 | -0.013 | 0.187 | 0.392 | 0.066 | N/A | 0.107 | 0.119 | -0.013 | -0.055 | 0.015 | 0.475 |
| | (18.4) | (-2.61) | (-17.3) | | (30.4) | (6.78) | | (5.68) | (22.9) | (-3.56) | (-9.03) | (0.62) | |
| (13) 2010 | 0.027 | -0.001 | -0.011 | 0.234 | 0.349 | 0.053 | N/A | 0.121 | 0.100 | -0.012 | -0.039 | 0.066 | 0.499 |
| | (23.7) | (-0.37) | (-15.1) | | (26.7) | (5.42) | | (6.09) | (25.2) | (-3.88) | (-8.43) | (3.47) | |
| (14) 2011 | 0.027 | -0.002 | -0.010 | 0.239 | 0.340 | 0.058 | N/A | 0.136 | 0.101 | -0.010 | -0.040 | 0.045 | 0.508 |
| | (24.1) | (-1.05) | (-13.8) | | (26.3) | (5.98) | | (6.48) | (25.0) | (-3.19) | (-8.77) | (2.29) | |
| (15) 2012 | 0.023 | -0.005 | -0.011 | 0.196 | 0.355 | 0.055 | N/A | 0.143 | 0.079 | -0.009 | -0.027 | 0.081 | 0.439 |
| | (18.8) | (-2.29) | (-14.3) | | (25.3) | (5.17) | | (5.72) | (16.4) | (-2.87) | (-5.08) | (3.15) | |
| (16) 2013 | 0.022 | -0.005 | -0.013 | 0.214 | 0.382 | 0.052 | N/A | 0.116 | 0.085 | -0.010 | -0.025 | -0.029 | 0.463 |
| | (18.9) | (-1.82) | (-14.9) | | (25.0) | (4.55) | | (4.30) | (18.4) | (-3.44) | (-5.01) | (-1.24) | |
| (17) 2014 | 0.023 | -0.006 | -0.011 | 0.254 | 0.367 | 0.051 | N/A | 0.107 | 0.079 | -0.014 | -0.022 | -0.016 | 0.514 |
| | (23.1) | (-2.64) | (-13.4) | | (25.7) | (4.62) | | (4.34) | (22.5) | (-5.19) | (-5.16) | (-0.83) | |
| (18) 2015 | 0.026 | -0.010 | -0.013 | 0.278 | 0.390 | 0.053 | N/A | 0.117 | 0.073 | -0.011 | -0.018 | 0.023 | 0.507 |
| | (24.0) | (-3.91) | (-13.9) | | (23.8) | (4.06) | | (3.97) | (20.1) | (-3.44) | (-3.79) | (0.94) | |

## Table 12: SDC Acquisition Investment-Q Regressions

The table reports 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 acquisition dummy, which is one if the given firm acquired any assets in the SDC Platinum database in the given year $t$. All RHS variables are ex ante observable in year $t-1$. In all, the results below are based on two distinct Q-models. The first block of four columns is the basic investment-Q regression where the SDC acquisition dummy is regressed on ex-ante Tobins Q and basic controls. The second block of 9 columns is the conditional model, where the SDC 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). $t$-statistics are in parentheses.

| | Basic Model | | | | Conditional Model | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 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 $R^2$ |
| (1) 1998 | 0.025 | -0.018 | 0.073 | 0.084 | -0.189 | -0.218 | N/A | -0.111 | -0.077 | 0.007 | 0.190 | -0.050 | 0.096 |
| | (6.61) | (-2.17) | (22.7) | | (-3.40) | (-4.69) | | (-1.01) | (-4.85) | (0.46) | (9.07) | (-0.64) | |
| (2) 1999 | 0.027 | 0.008 | 0.068 | 0.087 | -0.064 | -0.159 | N/A | -0.097 | -0.025 | -0.006 | 0.122 | 0.093 | 0.093 |
| | (8.83) | (0.90) | (21.5) | | (-1.12) | (-3.27) | | (-0.81) | (-1.82) | (-0.50) | (7.04) | (1.17) | |
| (3) 2000 | 0.021 | 0.012 | 0.068 | 0.101 | 0.058 | -0.131 | N/A | -0.215 | -0.023 | 0.025 | 0.068 | 0.042 | 0.110 |
| | (14.3) | (1.47) | (21.6) | | (1.02) | (-2.73) | | (-1.89) | (-3.05) | (3.70) | (7.33) | (1.22) | |
| (4) 2001 | 0.019 | 0.007 | 0.070 | 0.100 | 0.047 | -0.174 | N/A | -0.292 | -0.043 | 0.031 | 0.089 | -0.018 | 0.111 |
| | (8.38) | (0.82) | (23.1) | | (0.84) | (-3.70) | | (-2.73) | (-4.37) | (3.16) | (6.48) | (-0.32) | |
| (5) 2002 | 0.027 | 0.010 | 0.067 | 0.093 | -0.071 | -0.218 | N/A | -0.073 | -0.083 | 0.001 | 0.191 | 0.125 | 0.109 |
| | (7.49) | (1.19) | (21.3) | | (-1.17) | (-4.36) | | (-0.70) | (-5.42) | (0.10) | (9.43) | (1.61) | |
| (6) 2003 | 0.034 | -0.007 | 0.066 | 0.085 | -0.036 | -0.181 | N/A | 0.022 | -0.065 | 0.001 | 0.169 | 0.211 | 0.093 |
| | (6.79) | (-0.75) | (20.1) | | (-0.54) | (-3.31) | | (0.21) | (-2.87) | (0.07) | (6.06) | (2.26) | |
| (7) 2004 | 0.026 | 0.001 | 0.059 | 0.060 | -0.032 | -0.194 | N/A | -0.268 | -0.075 | 0.011 | 0.178 | -0.118 | 0.072 |
| | (5.80) | (0.06) | (16.3) | | (-0.43) | (-3.27) | | (-2.37) | (-3.65) | (0.75) | (7.32) | (-1.43) | |
| (8) 2005 | 0.027 | 0.013 | 0.068 | 0.073 | -0.139 | -0.234 | N/A | -0.195 | -0.030 | 0.013 | 0.117 | 0.008 | 0.079 |
| | (6.15) | (1.18) | (17.1) | | (-1.76) | (-3.69) | | (-1.61) | (-1.42) | (1.00) | (4.98) | (0.10) | |
| (9) 2006 | 0.035 | 0.007 | 0.074 | 0.083 | -0.229 | -0.195 | N/A | 0.065 | -0.053 | -0.004 | 0.192 | 0.181 | 0.092 |
| | (6.52) | (0.63) | (18.3) | | (-2.72) | (-2.99) | | (0.50) | (-2.09) | (-0.22) | (6.78) | (1.73) | |
| (10) 2007 | 0.018 | -0.007 | 0.071 | 0.077 | -0.229 | -0.287 | N/A | 0.158 | -0.048 | -0.005 | 0.137 | 0.114 | 0.087 |
| | (3.94) | (-0.69) | (17.7) | | (-2.81) | (-4.53) | | (1.25) | (-2.31) | (-0.37) | (5.87) | (1.14) | |
| (11) 2008 | 0.029 | 0.031 | 0.068 | 0.082 | -0.111 | -0.231 | N/A | -0.157 | -0.029 | -0.012 | 0.167 | 0.027 | 0.092 |
| | (6.58) | (2.97) | (17.3) | | (-1.39) | (-3.75) | | (-1.29) | (-1.38) | (-0.96) | (6.97) | (0.27) | |
| (12) 2009 | 0.053 | 0.009 | 0.063 | 0.082 | 0.045 | -0.202 | N/A | -0.111 | -0.087 | 0.019 | 0.235 | 0.197 | 0.092 |
| | (7.66) | (0.84) | (17.3) | | (0.57) | (-3.44) | | (-0.98) | (-2.76) | (0.83) | (6.38) | (1.38) | |
| (13) 2010 | 0.028 | 0.019 | 0.070 | 0.087 | -0.102 | -0.135 | N/A | -0.004 | -0.093 | -0.007 | 0.264 | -0.159 | 0.101 |
| | (4.53) | (1.68) | (17.5) | | (-1.17) | (-2.10) | | (-0.03) | (-3.51) | (-0.34) | (8.51) | (-1.27) | |
| (14) 2011 | 0.041 | 0.041 | 0.075 | 0.103 | -0.240 | -0.150 | N/A | 0.045 | -0.054 | 0.015 | 0.239 | -0.179 | 0.116 |
| | (6.69) | (3.50) | (18.3) | | (-2.72) | (-2.25) | | (0.32) | (-1.93) | (0.69) | (7.63) | (-1.34) | |
| (15) 2012 | 0.043 | 0.035 | 0.078 | 0.110 | -0.089 | -0.000 | N/A | -0.049 | -0.046 | 0.002 | 0.238 | -0.211 | 0.120 |
| | (6.83) | (2.89) | (18.6) | | (-1.01) | (-0.00) | | (-0.31) | (-1.53) | (0.10) | (7.20) | (-1.32) | |
| (16) 2013 | 0.028 | 0.016 | 0.067 | 0.080 | -0.109 | -0.120 | N/A | 0.027 | -0.066 | 0.006 | 0.178 | 0.151 | 0.087 |
| | (5.06) | (1.26) | (15.5) | | (-1.21) | (-1.78) | | (0.17) | (-2.45) | (0.39) | (6.11) | (1.11) | |
| (17) 2014 | 0.019 | 0.015 | 0.064 | 0.070 | -0.102 | -0.091 | N/A | 0.117 | -0.047 | 0.013 | 0.144 | -0.088 | 0.076 |
| | (3.74) | (1.21) | (14.4) | | (-1.10) | (-1.28) | | (0.74) | (-2.09) | (0.73) | (5.21) | (-0.72) | |
| (18) 2015 | 0.020 | 0.017 | 0.069 | 0.084 | -0.136 | -0.161 | N/A | 0.360 | -0.054 | 0.026 | 0.117 | 0.140 | 0.094 |
| | (3.96) | (1.39) | (15.7) | | (-1.49) | (-2.19) | | (2.17) | (-2.63) | (1.49) | (4.37) | (1.03) | |

## Table 13: SDC Acquisition Target-Q Regressions

The table reports results from annual OLS divestiture-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 divestiture dummy, which is one if the given firm sold any assets in the SDC Platinum database in the given year $t$. All RHS variables are ex ante observable in year $t-1$. In all, the results below are based on two distinct Q-models. The first block of four columns is a basic divestiture-Q regression where the SDC divestiture dummy is regressed on ex-ante Tobins Q and basic controls. The second block of 9 columns is the conditional model, where the divestiture 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). $t$-statistics are in parentheses.

| | Basic Model | | | | Conditional Model | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 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 $R^2$ |
| (1) 1998 | 0.003 | 0.052 | 0.045 | 0.080 | 0.025 | -0.043 | N/A | 0.113 | -0.017 | -0.005 | 0.039 | -0.065 | 0.084 |
| | (0.85) | (7.58) | (17.1) | | (0.56) | (-1.13) | | (1.26) | (-1.31) | (-0.38) | (2.25) | (-1.03) | |
| (2) 1999 | 0.004 | 0.060 | 0.044 | 0.080 | 0.082 | -0.031 | N/A | 0.455 | -0.019 | -0.007 | 0.028 | 0.102 | 0.090 |
| | (1.61) | (8.50) | (16.7) | | (1.72) | (-0.76) | | (4.58) | (-1.64) | (-0.71) | (1.95) | (1.52) | |
| (3) 2000 | 0.001 | 0.050 | 0.043 | 0.075 | 0.028 | 0.003 | N/A | 0.387 | -0.006 | -0.001 | 0.013 | -0.026 | 0.086 |
| | (1.02) | (7.57) | (16.8) | | (0.61) | (0.08) | | (4.18) | (-0.97) | (-0.20) | (1.67) | (-0.95) | |
| (4) 2001 | 0.001 | 0.050 | 0.040 | 0.073 | -0.003 | -0.077 | N/A | 0.375 | -0.013 | -0.005 | 0.025 | -0.023 | 0.085 |
| | (0.44) | (7.63) | (16.2) | | (-0.06) | (-2.01) | | (4.31) | (-1.58) | (-0.65) | (2.25) | (-0.51) | |
| (5) 2002 | 0.000 | 0.049 | 0.041 | 0.075 | -0.022 | -0.018 | N/A | 0.364 | -0.006 | -0.006 | 0.029 | -0.091 | 0.085 |
| | (0.02) | (6.81) | (16.1) | | (-0.45) | (-0.43) | | (4.29) | (-0.48) | (-0.57) | (1.78) | (-1.45) | |
| (6) 2003 | -0.001 | 0.050 | 0.042 | 0.076 | 0.028 | -0.050 | N/A | 0.306 | 0.010 | -0.012 | 0.016 | -0.119 | 0.093 |
| | (-0.25) | (6.29) | (15.6) | | (0.51) | (-1.12) | | (3.64) | (0.53) | (-0.91) | (0.69) | (-1.55) | |
| (7) 2004 | 0.001 | 0.055 | 0.047 | 0.092 | 0.017 | 0.022 | N/A | 0.595 | -0.002 | -0.010 | 0.035 | -0.104 | 0.110 |
| | (0.28) | (6.65) | (16.7) | | (0.29) | (0.47) | | (6.81) | (-0.12) | (-0.87) | (1.88) | (-1.63) | |
| (8) 2005 | 0.002 | 0.067 | 0.046 | 0.082 | 0.042 | 0.023 | N/A | 0.559 | -0.020 | 0.005 | 0.035 | -0.127 | 0.104 |
| | (0.43) | (7.43) | (14.1) | | (0.66) | (0.46) | | (5.72) | (-1.17) | (0.50) | (1.87) | (-1.84) | |
| (9) 2006 | -0.001 | 0.083 | 0.056 | 0.118 | 0.002 | -0.038 | N/A | 0.613 | -0.010 | -0.017 | 0.057 | -0.171 | 0.138 |
| | (-0.29) | (9.28) | (16.9) | | (0.03) | (-0.73) | | (5.83) | (-0.47) | (-1.16) | (2.47) | (-2.02) | |
| (10) 2007 | 0.003 | 0.071 | 0.049 | 0.091 | 0.118 | 0.152 | N/A | 0.763 | 0.005 | -0.017 | 0.030 | -0.014 | 0.116 |
| | (0.73) | (8.06) | (14.8) | | (1.76) | (2.93) | | (7.36) | (0.30) | (-1.52) | (1.55) | (-0.16) | |
| (11) 2008 | -0.006 | 0.047 | 0.036 | 0.053 | 0.123 | 0.035 | N/A | 0.719 | -0.011 | 0.003 | 0.013 | -0.259 | 0.077 |
| | (-1.57) | (5.49) | (11.0) | | (1.84) | (0.67) | | (7.03) | (-0.60) | (0.32) | (0.66) | (-3.14) | |
| (12) 2009 | -0.007 | 0.043 | 0.042 | 0.066 | 0.234 | 0.161 | N/A | 0.590 | 0.008 | -0.028 | 0.027 | -0.281 | 0.090 |
| | (-1.09) | (4.86) | (13.3) | | (3.46) | (3.18) | | (6.00) | (0.28) | (-1.41) | (0.85) | (-2.27) | |
| (13) 2010 | 0.004 | 0.068 | 0.054 | 0.101 | 0.112 | 0.155 | N/A | 0.563 | -0.047 | 0.001 | 0.067 | -0.023 | 0.117 |
| | (0.75) | (6.98) | (16.0) | | (1.53) | (2.85) | | (5.04) | (-2.12) | (0.07) | (2.57) | (-0.22) | |
| (14) 2011 | 0.011 | 0.052 | 0.059 | 0.105 | 0.086 | 0.200 | N/A | 0.517 | 0.002 | -0.013 | 0.082 | -0.274 | 0.122 |
| | (2.14) | (5.39) | (17.2) | | (1.18) | (3.64) | | (4.36) | (0.08) | (-0.73) | (3.18) | (-2.50) | |
| (15) 2012 | 0.001 | 0.056 | 0.052 | 0.085 | 0.157 | 0.189 | N/A | 0.761 | -0.051 | -0.011 | 0.086 | -0.145 | 0.101 |
| | (0.11) | (5.39) | (14.3) | | (2.09) | (3.34) | | (5.66) | (-1.97) | (-0.63) | (3.03) | (-1.06) | |
| (16) 2013 | -0.001 | 0.057 | 0.047 | 0.080 | 0.032 | 0.188 | N/A | 0.899 | 0.003 | -0.009 | 0.039 | -0.229 | 0.104 |
| | (-0.27) | (5.36) | (13.0) | | (0.43) | (3.32) | | (6.81) | (0.15) | (-0.69) | (1.59) | (-2.01) | |
| (17) 2014 | -0.001 | 0.064 | 0.050 | 0.090 | 0.114 | 0.180 | N/A | 0.963 | -0.021 | 0.010 | 0.034 | -0.152 | 0.112 |
| | (-0.15) | (6.14) | (13.6) | | (1.50) | (3.07) | | (7.34) | (-1.14) | (0.64) | (1.50) | (-1.52) | |
| (18) 2015 | 0.001 | 0.062 | 0.051 | 0.098 | 0.259 | 0.277 | N/A | 0.770 | -0.018 | 0.008 | 0.035 | -0.203 | 0.117 |
| | (0.24) | (6.31) | (14.2) | | (3.48) | (4.63) | | (5.72) | (-1.09) | (0.58) | (1.60) | (-1.85) | |

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.

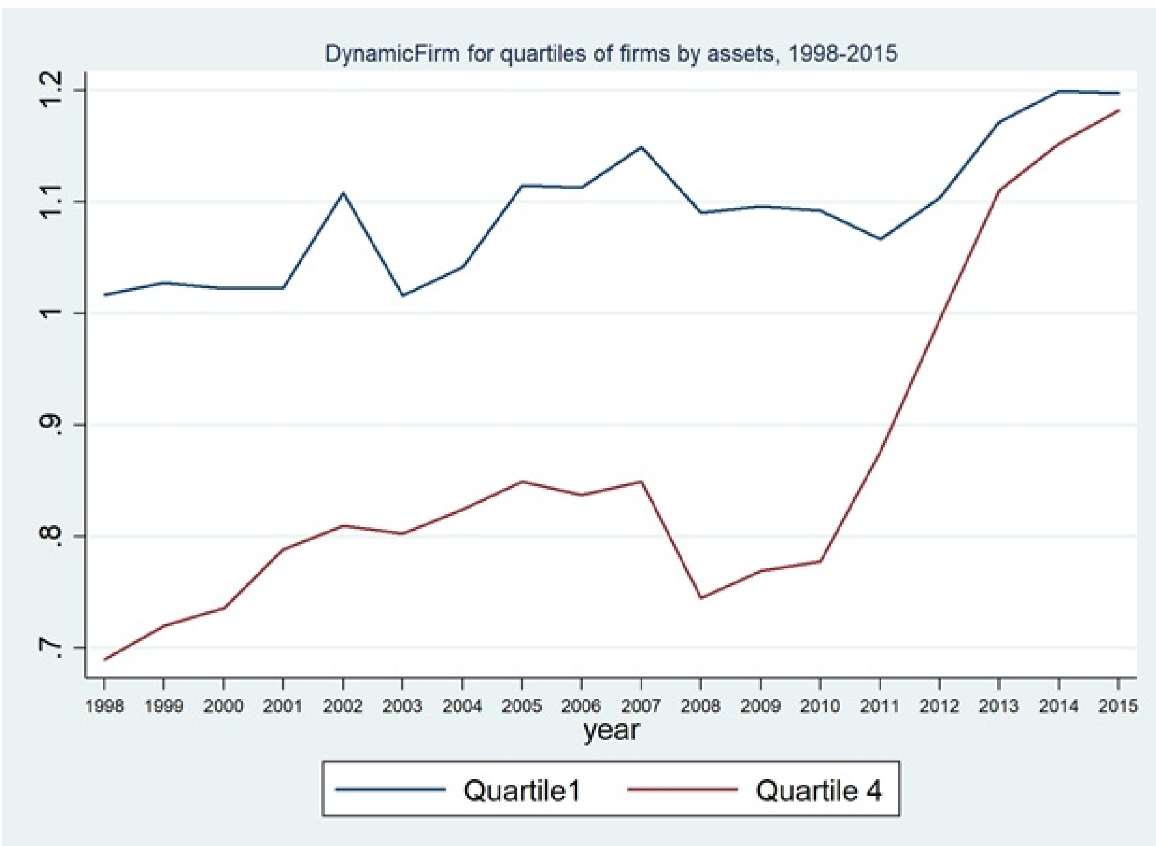
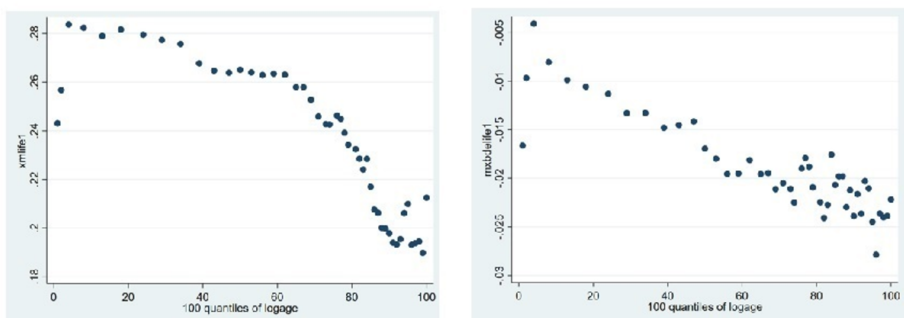
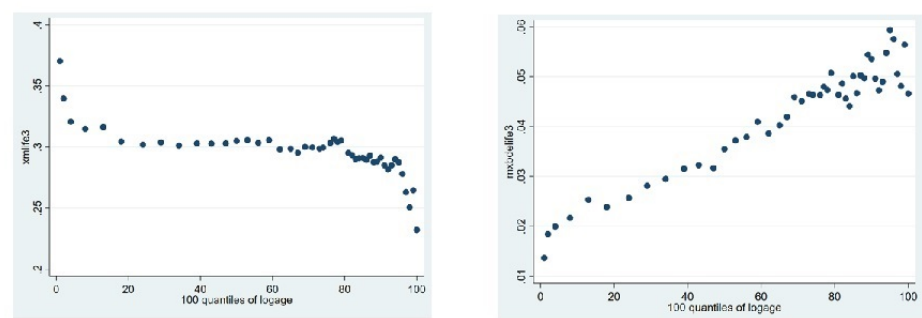


Figure 3: We report two graphs for each life cycle stage variable. The left graph for each plots the mean raw values against percentiles based on age for all sample firms. The right graph shows the mean values after each life variable is regressed on both firm and year fixed effects and then plotted against percentiles based on age. The former thus plots both within and across firm variation and the latter focuses on within firm variation only.

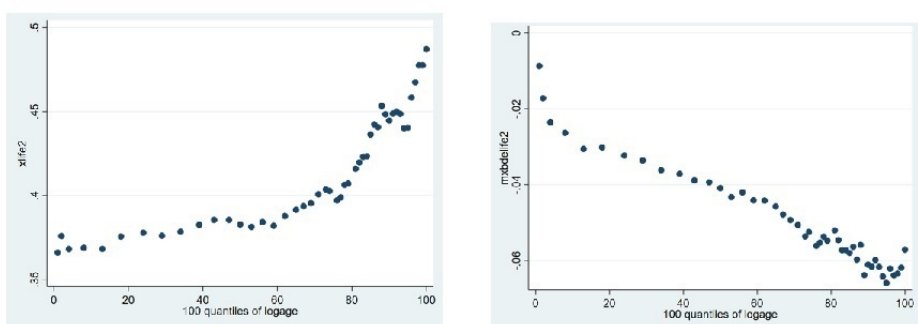
Life 1:




Life 3:




Life 2:




Life 4:

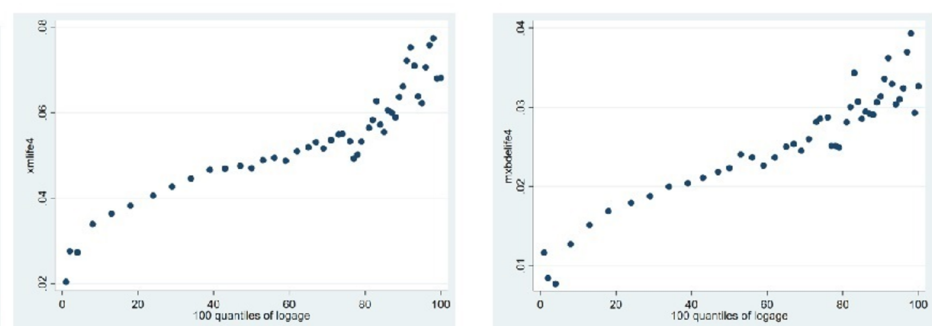


Figure 4: The figure displays the average level of CAPX/assets in time series for various subsamples. The subsamples are: full sample (top), the subsample with above median TNIC total similarity (middle), and the subsample with below median TNIC total similarity (bottom). Within each aforementioned sample, 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.

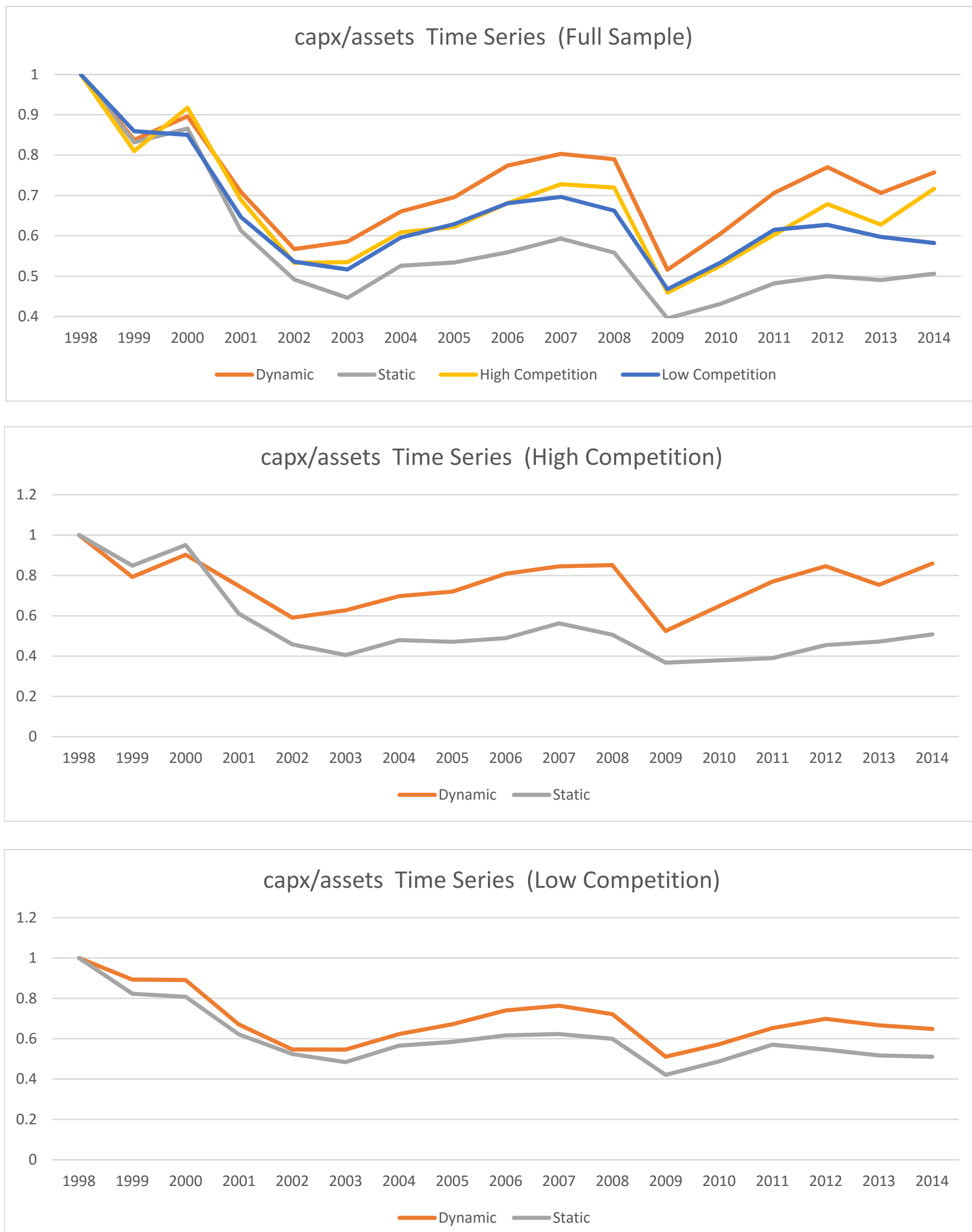


Figure 5: The figure displays the average level of R&D/assets in time series for various subsamples. The subsamples are: full sample (top), the subsample with above median TNIC total similarity (middle), and the subsample with below median TNIC total similarity (bottom). Within each aforementioned sample, 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.

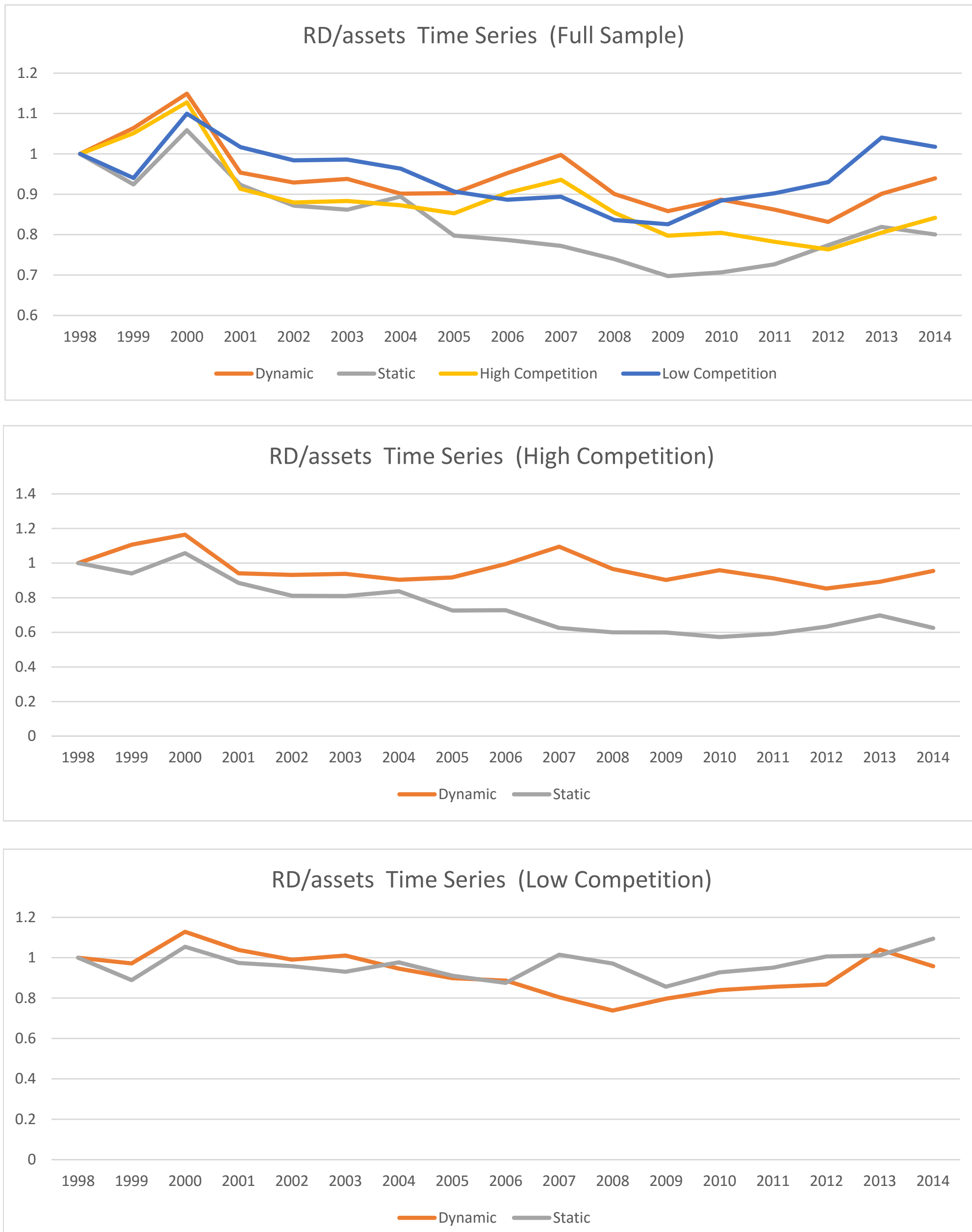
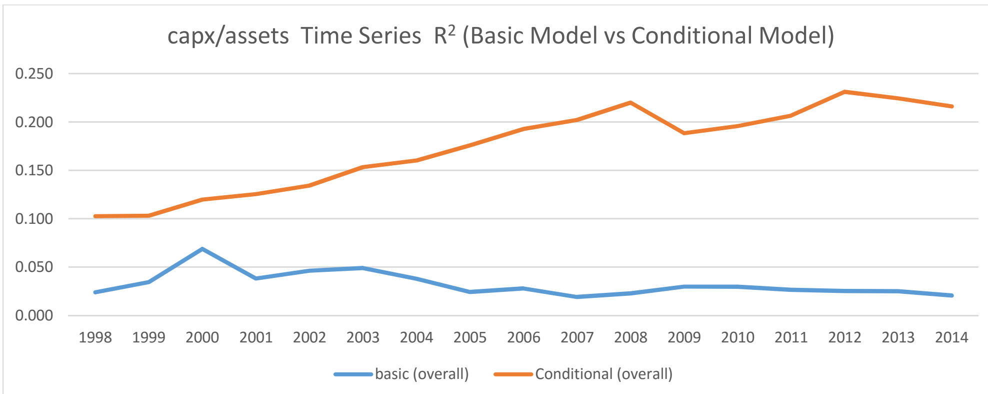


Figure 6: Plot of the $R^2$ of the annual cross sectional regressions in Tables 7 and 8. The Basic Classic model does not adjust for differences in the investment-Q relationship for different values of the life variables. The Conditional model adjusts for the level of the Life variables and their interaction with Tobin's Q.



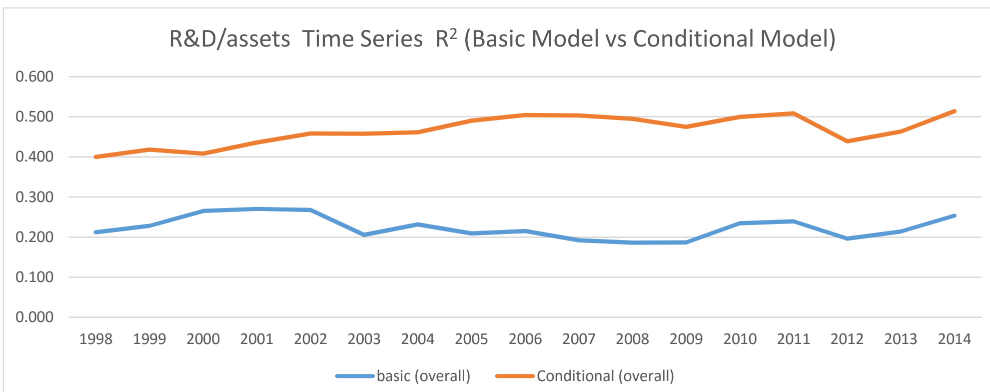
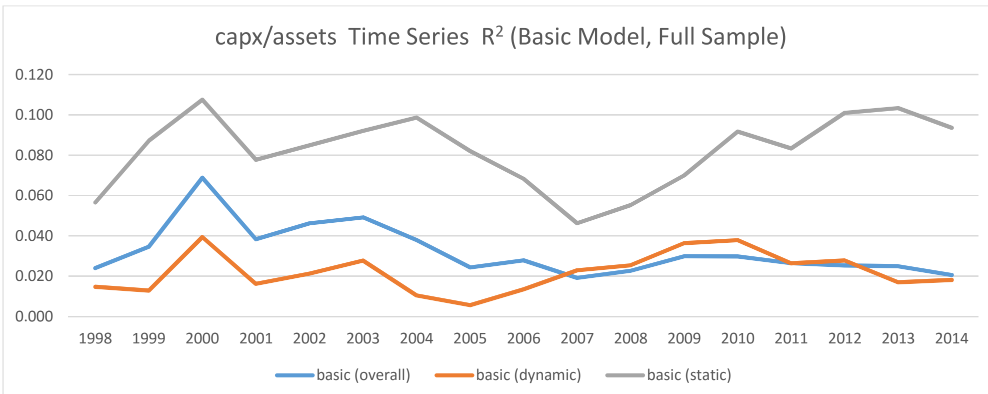
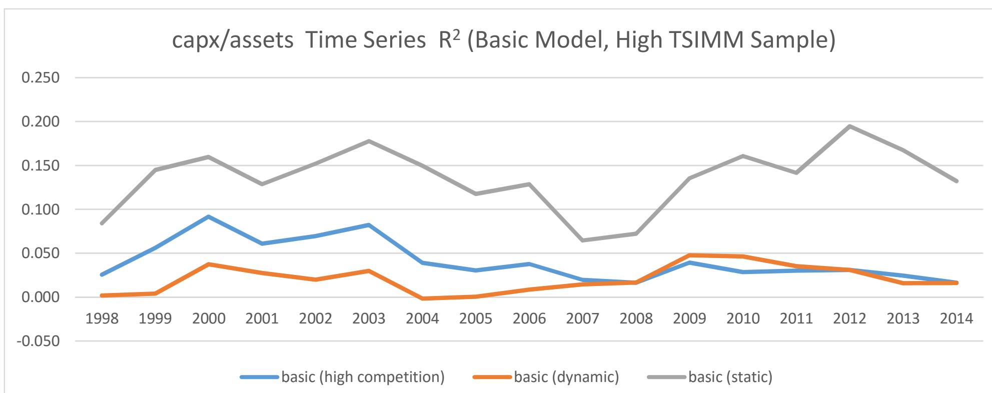



Figure 7: The figure displays the adjusted $R^2$ in time series from annual OLS regressions where the dependent variable is CAPX/assets, and Tobins Q is the key RHS variable. We also include controls for log assets and log firm age. All RHS variables are ex ante measurable from year $t-1$. The figure 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.



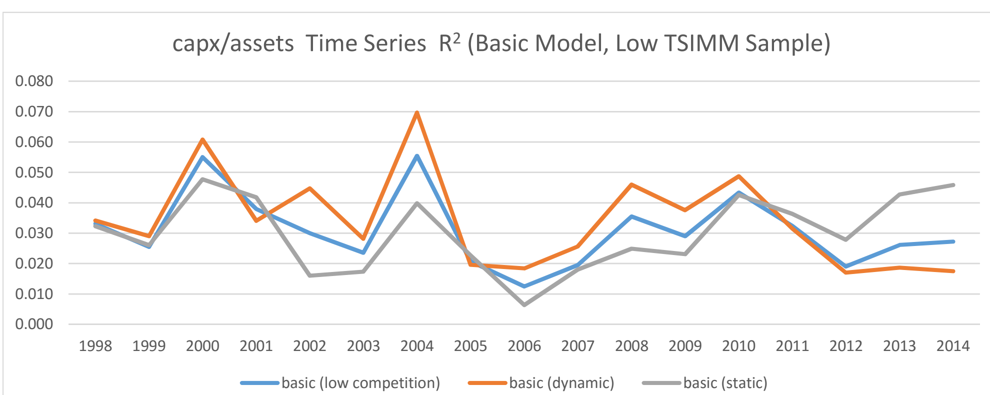



Figure 8: The figure displays the adjusted $R^2$ in time series from annual OLS regressions where the dependent variable is CAPX/assets, for three models. The first is the basic model, which includes Tobins' Q and the controls for log assets and log firm age. The age-quartile-based life cycle conditional 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.