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, and reveals a natural ordering of investments driven by the product life cycle. Firms initially focus on R&D, which additionally is sensitive to Q. CAPX emerges second. Acquisitions then arise as firms mature, and divestitures as firms decline. In aggregate, major shifts toward dynamic life cycle stages substantially explain the increase in the explanatory power of Q-models.

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 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?

We develop a novel 10-K text-based empirical model of firm life-cycles and test hypotheses motivated by a logical extension to the standard Q-theory of investment that conditions investment decisions on the firm's exposure to life cycle stages. Our analysis of 10-K text uses anchor-phrase methods, which were previously used in prior studies such as Hoberg and Maksimovic (2015) and Hoberg and Moon (2017). This approach identifies direct statements in firm 10-Ks that indicate the extent to which each firm has products that are in each of the four stages of the product life cycle indicated by Abernathy and Utterback (1978): product innovation, process innovation, maturity, decline. The result is a four element vector for each firm in each year, with elements summing to one, indicating which of the four life cycle stages the given firm's products are exposed to. Because firms can have multiple products in different life cycle stages, our approach captures the richness of each firm's overall product portfolio using continuous distributional measures. This richness also empowers us to measure the unique impact of each of the four life cycle stages on ex post investment strategies and outcomes, even controlling for firm fixed effects. We draw five major conclusions (none of which obtain using firm age as an alternative measure of life cycle stages):[3]

[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 Philippon (2017).

[3]As we discuss later, our approach is fully distinct from earlier life-cycle studies, such as Loderer, Stulz and Waelchli (2016), which use firm age as the principal state variable.

First, our text-based product life cycle model reveals a natural ordering of investment intensities and sensitivities to Q. Firms with exposure to the earliest product innovation stage invest heavily in R&D, and do so more intensively as their market valuations rise. As firms transition to the second process innovation stage, their CAPX becomes more sensitive to Tobin's Q. Firms with products in the third mature stage focus more on acquisitions, do so more intensively when Q increases. Finally, firms with products entering decline are more likely to be targets and sell their assets, but pull back from this activity and instead favor acquisitions when Q increases. This natural investment ordering indicates a progression from organic investment to inorganic investment over time. The results for declining firms indicate a gradual unwinding of the firm's assets and eventual delisting. However, this outcome is not inevitable as some firms escape or even reverse the cycle when their valuations rise.

Our second contribution is to show that major recessions, such as the technology bust and the financial crisis, induce faster progressions toward later stages of the life cycle. During the technology bust, these accelerated progressions are large, and in some cases firms shift from the earliest stages of the cycle all the way to the final stage of decline. During the financial crisis, shifts were more subtle as firms transitioned to a focus on efficiency and process (presumably to cut costs and preserve liquidity) and to a focus on maturity (presumably to reduce operating risk). Because we also find that life cycle exposures are sticky, these results suggest that there are long term consequences of major recessions as reduced innovation levels likely persist.

Third, conditioning on firm exposures to the life-cycle stages dramatically improves the performance of investment-Q models. The adjusted R^2 of our conditional CAPX Q-model is roughly 2x to 4x higher than the basic Q-model used in the literature, and this improved explanatory power furthermore increases significantly throughout our sample from roughly 10% to 20%.[4]

Fourth, we show that there has been a major shift in U.S. corporations that is

[4] This increase complements the findings of Gutierrez and Philippon (2017) and Andrei et al (2018).

new to the literature. During our sample period from 1998-2017, firms abandon the relatively static mature stage of the life cycle in favor of the three dynamic strategies: product, process and decline. This trend, which we refer to the rise of the dynamic firm, is strongest for larger and economically more important firms. This new stylized trend is relevant because it explains much of the aforementioned rise in explanatory power of our conditional-Q model over time. For example, both the level and the rate of increase in explanatory power are significantly larger for the sample of above-median dynamic life cycle firms.

Fifth, we show that the level of competition also moderates how firms with different exposures to the product life cycle respond to investment opportunities. Broadly and consistent with Gutierrez and Philippon (2018), both the level and the rate of increase in explanatory power of the conditional Q-model are higher for firms in more competitive product markets. Importantly, we also find that firm dynamism and competition are distinct in explaining these trends, as each explains roughly half of the trends in the Q model R^2 that we report.

To better understand our time series results, we examine if the shifts in life cycle dynamism and Q-model R^2 we report are related to several sectoral shifts in U.S. firm operations: increased production automation, outsourcing, focus on the supply chain, and competition for labor. We use anchor-phrase textual analysis of 10-Ks to measure each firm's exposure to these sectoral trends and we focus on shocks to distant peers to mitigate measurement error and firm-specific endogeneity. When we project life cycle dynamism onto these sectoral trend variables, we find that the explanatory power of our conditional model is strongly related to these trends, suggesting that the rise of the dynamic firm is related to changes in the organization and operating practices of corporations.

Although there are noteworthy exceptions, decades of empirical research have relied on highly aggregated measures of investment opportunities. Many important results have been established, but a critical issue is that such ratios treat firms as homogeneous and do not provide metrics for predicting differences in the investment activities of firms at different life cycle stages. 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 innovative approach below, and note that our approach is distinct but complementary to theirs. In contemporaneous work, Andrei et al (2018) propose 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.

We validate our life cycle model by demonstrating a strong relationship between our life cycle variables, firm age, and observed 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 and decline occur later. The size of the firm's 10-K product description grows significantly when the firm is in the product innovation stage, and shrinks when the firm is in the declining stage. These results are consistent with our life cycle variables modeling the specific stages suggested by Abernathy and Utterback (1978).

The novel investment and acquisition patterns we document do not obtain if a researcher models the life cycle using low-dimensional constructs such as firm age. This is because our findings indicate sharply non-linear shifts in investment opportunities across the life cycle stages. To illustrate this point, we construct an alternative four-stage life cycle based on annually sorting firms into age-based quartiles. This alternative model is not informative. Moreover, age progresses deterministically, whereas a given firm's true life cycle stage exposures is stochastic. Only models based on actual life cycle exposures can allow researchers to assess the impact of shocks, which in some cases can even induce firms to shift backwards in the cycle toward earlier stages. Because our results cannot be obtained using age alone, they 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 future research on innovation, growth opportunities, firm organization, and macro shocks.

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 in 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, physical plant, and acquisitions. 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 generally 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.

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

We posit that, for each stage of the life cycle, the firm optimizes its organization and policies to maximize value. As a foundation, we consider Jensen and Meckling (1976) definition of the firm as a ”nexus of contracts.” In our setting, these contracts incentivize the optimal set of activities for the firm's agents aimed at realizing the maximum value of the product portfolio given its life cycle stages. The resulting contracts and activities will vary as products go from a development to a mature stage, and to a declining stage. Given these contracts and activities, the firm must navigate shocks, acquire assets, hire employees, set its marketing strategy and its supply chain to optimally pursue the value maximization objective.

A primary goal of our paper is to accurately identify these product stages, and then econometrically analyze the composition of the activities firms pursue and how they relate to investment decisions.[6] In our empirical implementation, we posit that the frequency of mentions of processes and actions associated with each of the stages in Abernathy and Utterback (1978) provides a sufficiently rich metric of the underlying life cycle stage. We design our metrics to uniquely measure the stage distribution of a firm's product portfolio and nothing more, as this is the primitive exogenous concept laid out in the life cycle theory and our application of the nexus of contracts. We explicitly exclude verbal mentions of specific investments such as R&D and capital expenditures, which might or might not be used as endogenously selected tools to achieve the life cycle goals. Below we describe the metric and these exclusions, and we conduct several validation tests.

In our econometric analysis, we not only characterize the investment policies undertaken by firms in different life cycle stages, but we also examine the impact of major exogenous shocks including the two NBER recessions that our sample brackets: the dot com crash and the 2008 financial crisis. The dot com crash is particularly interesting in our setting as it likely indicates a shift in the product life cycle toward

[6]We note that the particular operational mix of strategies required to implement an objective over time may change. For example, to implement efficient processes a firm might in the past have hired many clerks and then, as technology develops, switched to computers. However, in our annual regressions we posit that these changes are slow enough to be considered second order.

late stages as many products created in the tech boom became obsolete or faced declining demand. The above-mentioned theory predicts that such a large plausibly exogenous shock can help to establish progression in the life cycle that are more likely to be causal in nature. In a separate test, we also consider plausibly exogenous shocks relating to broad sectoral shifts in automation, outsourcing, and labor competition.

2.1 Related Literature

Our paper is also related to recent work on life cycles measured using firm age. Loderer, Stulz and Waelchli (2016) argue that, as firms age, they become more rigid and less able to respond to growth opportunities.[7] Product market competition slows this process whereas investor monitoring speeds aging as firms must prioritize investor relationships. Arikan and Stulz (2016) show that 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 primary issuance motive (see DeAngelo, DeAngelo and Stulz (2010)). However, we also show that a comprehensive model of product life cycles generates many novel and economically large findings.

Our analysis is motivated by the Q-theory of investment (Hayashi (1982)). This theory predicts that the firm's investment opportunities can be measured as the ratio of the firm's market value to the cost of reproducing the firm's assets.[8] 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 theoret-

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

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

ically. 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 might have a high market value but might not purchase production facilities before it has a product (or even afterwards if the firm outsources production). Also, 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 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 Philippon (2018) argue that increases in market power weakened investment-Q relationships. 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.[9] Our approach differs as we focus on the product life cycle, but we also show that it complements the role of market power in explaining the relation between investment and Q.

Our paper is also related to a growing literature documenting large-scale changes in US firms over time. 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 organizational structure and R&D (see also Autor et al 2016).[10] 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 studies also focus on how management characteristics affect firm performance.[11] Our study suggests that some of these changes might also be related

[9]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 noted by Maksimovic (1988).

[10]See Bloom, Draca and Van Reenen (2016) for a study on European firms.

[11]See Bertrand and Schoar (2003), Prez-Gonzlez (2006), Bennedsen et al. (2007), Malmendier, Tate, and Yan (2011), Levine and Rubinstein (2017), Bloom and Van Reenen (2007, 2010), and Bloom et. al. (2013).

to shifts in life cycle stages.

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, while producing output that is easy to interpret.[12] 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 2017. We exclude financial firms (those with SIC codes in the range [6000,6999]). After further limiting the sample to firm-years with machine readable 10-Ks (both current and lagged), non-missing data on operating income and Tobin's Q, sales of at least $1 million, and assets of at least $1 million, we are left with 68,899 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.

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

3.2 The Product Life Cycle

Our goal is to use direct textual queries 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 a high 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 are a significant component. A firm in the third maturity stage should be characterized by discussions of continuation and market share, but without reference to product or process innovation. Finally, a firm in the fourth stage 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.

We construct our measures of product life cycle to ensure that they identify the life cycle exposures of the firm's products, and that they are not mechanically related to investment activities. To do so, we first exclude from consideration all

10-K paragraphs that explicitly mention capital expenditures or R&D. In particular, we exclude paragraphs from all of our life cycle queries if they contain the following phrases (our results are also robust to skipping this step):

General Exclusions: capital expenditure* OR research and development

To measure the firm's loading on the first stage "Life1", we identify all paragraphs in a firm's 10-K (after applying the above exclusions) that contain at least one word from each of the following two lists (an "and" condition, not an "or" condition).[13]

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 (after above exclusions) that contain at least one word from the following 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 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.

[13]Note that Life1 is focused on providing a metric on changes in the firm's product line, an output, and not on inputs like R&D or advertising expenditures.

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 in 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 over all four. The result is a four-element vector for each firm-year $\{Life1, Life2, Life3, Life4\}$ that sums to one. All four exposures are non-negative and are bounded in $[0, 1]$.

We also examine the absorbing state of delisting ("LifeDelist"). Specifically, we focus on delistings due to poor performance, which include 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. Our results are not highly sensitive to including or not including this variable as a control in our regression analysis.

3.3 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 (2018) 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) use estimates of intangible capital investment to provide novel measures of Q that take into account capital stocks of both tangible and intangible capital. Investment in intangibles consists of 20% of SG&A expenses and 100% of R&D expenses in each year, and these stocks then depreciate at 15% to 20% per year. This approach has many advantages, but it can also confound interpretations in our context. For example, we expect the nature of R&D and SG&A to vary over the life cycle. High SG&A in the early stages might build organizational capital, whereas it might reflect high costs of sales in the later stages. Also, a firm with high recent investments in intangible capital might transition to maturity, making the adjustments potentially stale or inadequate regarding their predictive power. To avoid any confounding interactions between the product life cycle itself and measures of Q, we estimate Q using the most generic approach possible, as discussed above. However, in our Online Appendix, we show that we obtain similar results if we instead use the Q from Peters and Taylor. Our results are also robust to the Erickson and Whited (2000) measurement error adjustment.

3.4 Policy and Outcome Variables

We examine four investment policies: R&D/assets, CAPX/assets, the decision to acquire assets, and 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 partial-firm asset acquisition data from SDC Platinum. SDC Acquirer is an indicator equal to one if the given firm acquires any assets from any seller (public or private) in the given year and is zero otherwise. Analogously, SDC Target is an indicator equal to one if the given firm sells any assets to any buyer (public or private) in the given year and is zero otherwise. Both variables include transactions involving parts of firms or whole firms.

3.5 Summary Statistics and Correlations

Table 1 displays summary statistics for our 1997 to 2017 panel of 68,899 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). Discussions of product decline are less common and make up 6.7% of the total text devoted to all four stages. The delisting rate due to poor performance is 2.7% in our sample.

[**Insert Table 1 Here**]

Investment rates are also consistent with existing studies. The average firm spends 5.9% of its assets on R&D, and 6.1% of its assets on CAPX. Roughly 34% of firms in our sample participate in acquisitions (partial or full), and 18.9% of firms sell at least some assets (both acquisition variables include public and private targets). The average Tobin's Q in our sample is 1.86.

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 (-22.4%) and Life4 is positively associated with firm age (15.3%). 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) has close to zero correlation. 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 closer to the theoretical predictions when we focus on within-firm variation (and control for firm fixed effects). For example, for a given firm in time series, process innovation precedes product maturity on average.

[**Insert Table 2 Here**]

The table also echoes our finding that firms in different stages of the life cycle focus on very different investments. Life1 firms focus heavily on R&D (55.3% correlation) and Life2 firms focus on CAPX (27.3% 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.

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 failed to expand fully. In contrast, large firms are engaged in multiple activities across many markets and thus might exhibit different life cycle exposures.

[**Insert Figure 1 Here**]

As expected, Figure 1 shows that small firms have higher values of Life1 than large firms. Also as expected, large firms have higher values of Life2 than small firms. Life2 is also rising over our sample period for larger firms, indicating more focus on process. Figure 1 also shows that Life3 is initially much higher for large firms, but it also declines significantly over time. By the end of our sample, the gap between the large and small firms has almost fully closed. Our findings indicate a major transition for large firms during our sample period that is new to the literature.

Intuitively, Life4 increases dramatically after the technology bust and then remains at the elevated levels and gradually declines through the remainder of our sample. The concurrent increase in Life4 and delisting rates is consistent with higher restructuring, obsolescence and failure during this period.

The strong shift away from the inactive mature stage Life3 and toward the other other stages is consistent with larger firms becoming more dynamic. In particular, Life1, Life2, and Life4 are dynamic as they all entail ongoing refinements of product and process portfolios. We thus define a firm's Dynamism Index as the total exposure to these active stages:

$$Dynamism\ Index = (1 - Life3). \tag{1}$$

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 more dynamic than large firms, but this gap later vanishes as larger firms become more dynamic and small firms are stable. We conclude that large firms have undergone a major transformation, especially in the first half of our sample.

[**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 an 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 at 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, product innovation (Life1) should precede process innovation (Life2), which 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. Results are presented in Table 3 and we cluster standard errors by firm.

[**Insert Table 3 Here**]

The results for firm age in Panel A support the Abernathy and Utterback (1978) life cycle. These tests control for both firm and year fixed effects, and we find that Life1 and Life2 are negatively related to 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 focal for younger firms. Later, firms transition to stability and decline. Our inferences are little-changed with additional controls in Panel B.

The only unexpected finding in Table 3 is that the coefficient for Life2 is more negative than the coefficient for Life1. One explanation is that much product innovation occurs when firms are still private, which we do not observe, influencing the computed link to firm age in this direction. Another explanation is that many young firms face financial constraints and hence need to pay at least some attention to cost cutting and process in order to preserve liquidity. Hoberg and Maksimovic (2015) and Hadlock and Pierce (2010) show that these younger and more innovative firms indeed appear to suffer more from financial constraints than do other firms.

Figure 3 reports average life cycle exposures as we increase firm age using age percentiles on the x-axis. The leftmost graph for each variable plots the 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 oriented. This reinforces the importance of including firm fixed effects when making life cycle inferences.[14]

[Insert Figure 3 Here]

In a second validation test reported in Online Appendix Table IA.1, we examine if our life cycle variables predict changes in the size of the firm's product portfolio in the next year. Following Hoberg and Phillips (2010), we measure product portfolio growth as the logarithmic growth in the size of the 10-K business description. We predict and find that Life1 positively predicts and Life4 negatively predicts product description growth. These results are highly significant at well-beyond the 1% level despite the inclusion of controls and firm fixed effects. Unlike Life1, lagged R&D expenditures does not predict product portfolio expansion, further illustrating that our life cycle variables are unique.

Overall, our results strongly validating our life cycle variables given the product life cycle depicted in our framework based on Abernathy and Utterback (1978). This

[14]Controlling for the stable part of a firm's disclosure (the firm fixed effect) is also important given Cohen, Malloy, and Nguyen (2018)'s findings that even small changes in disclosure are highly informative about future outcomes.

conclusion is reinforced by the fact that we use highly specialized textual searches targeting life cycle content alone, which maximize interpretability of these variables in this intended context.

5 NBER Recessions and Life Cycle Dynamics

We next examine whether major exogenous shocks can impact firm product portfolios in the life cycle. For example, do firms mature prematurely following recession shocks, or do they focus on process to cut costs? We consider two well-known NBER recessions that occurred in our sample period. The first is the technology bust NBER recession which begin in March 2001 and ended in November 2001. As our sample is yearly, we thus compare 2001 (recession period) to the prior three year period (1998 to 2000). The second is the financial crisis NBER recession, which began in December of 2007 and ended in June of 2009. We thus compare 2008 to 2009 (recession period) to the prior three year period (2004 to 2006). Although it does not materially impact our results, we omit 2007 from this test as the NBER recession officially began at the very end of 2007 making it ambiguous.

We examine if these recession shocks impact evolution across life cycle stages using both a transition matrix and a regression-based test. We identify a firm's ex-ante life cycle stage as Life1 if its de-meaned value of Life1 is higher than the de-meaned values of the other four life stages (we create similar ex-ante dummies for the other stages). To examine ex post transitions, for each firm, we compute raw transitions as the difference between the current firm-year's 4-element life vector minus the firm-year's life vector in the previous year. Our first ex post dependent variable, "Toward Life1" is one if the difference in Life1 is more positive than the difference for the other three stages. We compute similar dummy variables for the other three stages.

[Insert Table 4 Here]

In our multivariate regressions displayed on the left-hand side of Table 4, we regress these ex-post transition dummy variables on the ex-ante life cycle stages of the firm, their interactions with the post-treatment recession dummy, and controls for size, age, and Frame-French-48 industry and time fixed effects. All standard errors are clustered by firm. To preserve space, we only report the coefficients and t-statistics for the key interaction terms.

We also report raw transition matrix changes. For firms binned into each of the four ex-ante stages, we compute the average values of the four ex-post transition dummy variables ("Toward Life 1" etc). The result is an annual 4x4 directed transition matrix. To assess the impact of each NBER recession, we simply consider the difference in transitions computed as the values of this matrix in the recession period for each shock minus the values of this matrix in the pre-treatment period. We report these transition differences in the last four columns of Table 4. In general the regression and transition matrix frameworks produce consistent results.

Panel A of Table 4 displays the results for the technology bust. The table shows that the recession led to a uniform accelerated progression of more innovative Life1 firms toward late stages of the life cycle, especially product decline (Life4) relative to the pre-recession period. These results are significant at the 1% level. Life2 and Life3 firms transitioned significantly less toward Life1 and more toward Life4. Although almost all results favor late stage progressions, one minor exception is that Life3 firms transitioned more to Life2. This finding is consistent with some preference for liquidity-preserving cost cutting during recessions. The transitions on the right side of Table 4 shows that these results are economically large. For example, the likelihood that an ex ante Life1 firm will transition toward Life2 or Life4 increases by 6.4 and 8.2 percentage points, respectively. These results are intuitive given the tech bust ended with the failure of many products. They also illustrate the severity of the real consequences of significant recessions.

Panel B of Table 4 shows that the financial crisis also led to an acceleration of the life cycle, although the specifics are different. Life1 firms shifted more toward maturity (Life3) and were less likely to shift to Life2. This is consistent with ceasing product investment and favoring stability and risk reduction. This is also consistent with the well-known goal of preserving financial liquidity at this time. Life2 firms were more likely to remain focused on process and were less likely to shift back toward Life1, which is also consistent with less risk taking and using process revisions to reduce costs and preserve liquidity.

Perhaps the most interesting finding in Panel B is that life4 firms appeared to become somewhat opportunistic and transitioned toward the earlier Life2 stage. One interpretation is that these firms were able to take advantage of the increased financial constraints of their peers. In particular, Hoberg and Maksimovic (2015) suggest that more innovative firms faced more severe constraints. Hence the shrinking Life4 firms likely enjoyed better liquidity at this time given their retained earnings and proceeds from recent asset sales, making them more agile when other firms are less agile. As these results are suggestive, they motivate future research on potential opportunism by declining Life4 firms seeking a return to sustainability.

6 Investment and the Product Life Cycle

In this section, we consider panel data regressions with firm and year fixed effects to formally examine ex post firm investment decisions given ex ante product life cycle exposures. Table 5 reports results from investment-Q regressions. The dependent variable is R&D/assets (Panel A), CAPX/Assets (Panel B), the SDC Acquisition Dummy (Panel C), and the SDC Target Dummy (Panel D). Given recent evidence that U.S. industries are becoming more concentrated (Grullon, Larkin and Michaely (2016)) and the relevance of this trend for Q-models (Gutierrez and Philippon (2017)), we report results for the full sample and subsamples based on high and low competition (measured using TNIC-3 HHI, see Hoberg and Phillips (2016)). The RHS variables include ex-ante life cycle variables, interactions with Tobin's Q, and controls for size and age. Tobin's Q is re-centered at its annual sample mean so that the life cycle coefficients are interpretable as the impact of a one sigma shift of the given life cycle variable on the dependent variable for a firm having an average Q in its given year.[15]

In Table 5 we first show the basic OLS Q-model regressions where the dependent variable is CAPX/assets, and Tobin's Q is the key RHS variable. We include size and age controls, as well as firm μ_i and year λ_t fixed effects:

$$[\frac{CAPX}{Assets}]_{i,t} = \alpha_0 + \alpha_1 Q_{i,t} + \alpha_2 Log[Assets_{i,t}] + \alpha_3 Log[Age] + \lambda_t + \mu_i + \epsilon_{i,t} \tag{2}$$

We also show our conditional model, which adds the life cycle stages to the basic model and also replaces Tobin's Q with four cross terms equal to Tobin's Q multiplied by each of the life cycle stages. The interpretation as a conditional model arises because the life cycle stages sum to unity.

$$[\frac{CAPX}{Assets}]_{i,t} = \alpha_0+\alpha_1 Life1_{i,t}+\alpha_2 Life2_{i,t}+\alpha_3 Life4_{i,t}+\alpha_4 Life1_{i,t}\, Q_{i,t}+\alpha_5 Life2_{i,t}\, Q_{i,t}$$
$$+\alpha_6 Life3_{i,t}\, Q_{i,t}+\alpha_7 Life4_{i,t}\, Q_{i,t}+\alpha_8 Log[Assets_{i,t}]+\alpha_9 Log[Age_{i,t}]+\lambda_t+\mu_i+\epsilon_{i,t} \tag{3}$$

[Insert Table 5 Here]

Panel A of Table 5 focuses on R&D/assets. As expected, we find that Life1 firms invest more heavily in R&D relative to other firms, and their Q-sensitivity to R&D is also positive and significant across the specifications. However, unique to our study, we also find that *only* Life1 firms have a positive Q-sensitivity to R&D. Exposure to the other three stages indicate insignificant or negative Q-sensitivities. Because only 25% of all products are in the Life1 stage (See Table 1), this implies that Q-sensitivity to R&D is highly conditional on the life cycle. More starkly, Life3 firms have a negative and significant Q sensitivity to R&D. This result is novel given the literature, which reports uniformly positive Q-sensitivity to R&D. This result suggests that when Life3 firms experience a rise in Q, one should expect increases in other value-adding activities (such as acquisitions as noted below) and not R&D specifically. This suggests that the end-stages of a project may signal different value maximization strategies.

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

Turning to CAPX in Panel B, we find that Life2 firms have the highest Q-sensitvity. Life3 and Life4 firms also have positive and mostly significant Q-sensitivities, but the coefficients are only one third as large in magnitude. In contrast, most specifications indicate a negative and significant Life1 Q-sensitivity to CAPX. This suggests that a shift by Life1 firms away from R&D and toward CAPX would signal a decline in growth options and a lower valuation. A similarly rich interpretation obtains for Life3 firms and R&D as noted above. For example, lower (not higher) valuations for Life3 firms predict increased R&D, which is consistent with using R&D to defend the firm against emerging product market threats. When Life3 firms have higher valuations, they do not focus more on R&D, but rather they focus on CAPX and acquisitions, which are likely more value-creating when product markets are stable.

Panel C of Table 5 examines investment in acquisitions as the dependent variable. We find that Life3 and Life2 firms have the highest Q sensitivity. Life4 firms are also somewhat sensitive to Q, and Life1 firms are significantly 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, and in some cases, signs reverse for intuitive reasons. The high acquisition sensitivity of Life3 firms to increased Q is consistent with the investment life-cycle ordering that we document, as more mature firms face a dry-well problem on organic investment and hence focus on inorganic investment in the form of acquisitions. Life1 firms are negatively sensitive to acquisitions, as high valuations reflect the best possible growth options in product development rather than in costly acquisitions. Our results for Life4 suggest that increased market values signal that acquisitions or CAPX might offer investment options to potentially shift these firms back to sustainable life cycle stages.[16]

Panel D shows the results for asset sales (targets of acquisitions) as the dependent variable. Our main result is that Life4 firms, facing decline, experience a higher rate

[16]Because Tobins Q contains information about valuations, a concern is that our results might be driven in part by motives to use overvalued stock as a means of payment in acquisitions. In unreported tests, we remove transactions that use stock as a means of payment from our sample and we find that our results are fully robust.

of asset sales. Turning to Q-sensitivity, we find evidence that these same Life4 firms divest fewer assets as Q increases. Overall the results for asset sales further suggests that firms in later stages of the life cycle eventually face 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, especially when their Q also declines. Hence their value maximizing strategy is to dis-invest assets through sales and unwind the firm. However, if new opportunities emerge, these firms are ready to become acquirers and invest in CAPX to shift to sustainable life cycle stages. Firms that fail to do so are acquired or eventually delist.

Table 5 also shows that our findings are uniformly stable across competition subsamples. We conclude that competition, while important, has distinct effects on investment and cannot explain our results. Rather, our results are consistent with the economic intuition of the Abernathy and Utterback (1978) life cycle stages. We also note that our results cannot be discerned using firm age alone given they are highly nonlinear across the stages and because age is only moderately correlated with life cycle stages (we show direct evidence on this conclusion regarding firm age in the next section).

The Online Appendix shows robustness to (1) using Tobin's Q as measured by Peters and Taylor (2017), (2) using the Erickson and Whited (2017) measurement error correction, and (3) including lagged investments and their interactions with Q as controls (using both least squares and the Blundell and Bond (1998) correction for the correlation between lagged dependent variable and the firm fixed effect). This latter test ensures that our life cycle variables contain novel content that is not mechanically related to investment policies. Also, since controlling for size is not directly motivated by life-cycle models, we test and confirm that our results are robust whether we include or exclude size as a control.

We conclude that investment follows a natural ordering through the product life cycle, and this order strongly determines the relevance of investment-Q models across various types of investment. Life1 and Life2 are associated with organic investment in the form of R&D and CAPX. As firms mature to Life3, they focus on inorganic investment, and eventually on asset sales as they enter decline.

Another novel result in our paper is that we find that some investments are significantly negatively sensitive to Q in some states, and these results reveal intuitive and important trade offs that firms must make over the life cycle. Acquisitions of Life1 firms have negative Q sensitivities, reinforcing the importance of product development for these firms, and illustrating why an acquisition can be a negative signal for the market. We also observe negative R&D sensitivity to Q for Life3 firms, which is also new given the existing literature, which reports only strong positive Q-sensitivities for R&D. This result likely reflects the intuition that a mature firm initiating R&D likely faces negative developments to its previously-stable markets, such as disruption or competitive shocks. Finally, the negative sensitivity of Life4 to asset sales indicates a path to ultimate delisting if valuations remain low, but also a more opportunistic path back to sustainability if valuations rise, as these firms then shift toward acquisitions and CAPX.

6.1 Economic Magnitudes

In this section, we evaluate the economic significance of our earlier findings regarding sensitivity to Tobins Q. Table 6 reports the results. The first two columns report the investment policy being analyzed, and the average value of the dependent variable. To report Q sensitivities in the next four columns, we first sort firms annually 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.

[Insert Table 6 Here]

We find the highest responsiveness of R&D to Q in Life1 firms – about two to three times greater than for high Life3 and Life4 firms. The CAPX responsiveness is highest for Life2. Life3 firms have the highest Q-responsiveness for acquisitions, and Life4 have the highest (negative) Q responsiveness for asset sales. In each case the magnitude of the highest economic effect is substantially above that of the others.

6.2 Firm Age based Life Cycle Model

We next explore whether a classical age-based life-cycle model can explain our results. We thus re-run our main specifications from Table 5, replacing the four text based life cycle variables with four age-based life cycle dummy variables. Each dummy respectively indicates the age quartile, based on annual sorts, the firm belongs to. Life1 indicates the youngest firms and Life4 the oldest firms. The results are reported in Table 7, which shows that oldest firms are most responsive for acquisitions and asset sales, and less responsive for R&D. Otherwise the table shows little of the richness observed in our conditional model in Table 5. In particular, most sensitivities do not vary materially across the age quartiles, and we do not observe a single sign reversal across the quartiles for any of the four policies. We thus conclude that our more refined text-based life cycle is required to analyze firm responses.

[**Insert Table 7 Here**]

7 Implications for Investment-Q Models

In this section, we follow studies such as Gutierrez and Philippon (2017) and Lee, Shin and Stulz (2016) and examine how the cross-sectional relationship between Q and corporate policies varies over our sample period, especially when we condition on the life cycle stages. Our specifications are annual cross-sectional regressions analogous to the specifications in equations (2) and (3) above, but omitting year and firm fixed effects. We focus on explanatory power measured as the adjusted R^2

(henceforth R^2 for parsimony) of these models. The results are displayed in the first four columns of Table 8. Consistent with Gutierrez and Philippon (2017), we find that the R^2 initially peaks early in our sample around 2000 at 2.0% and then later declines thereafter to 0.8% by the end of our sample.

The nine columns on the right of Table 8 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 increasing and is almost an order of magnitude larger than that of the basic model. A likelihood ratio test indicates that this difference in R^2 is statistically significant at the 1% level in each year. We conclude that the life cycle plays an increasingly important role in the CAPX Q-model during our sample. The upper graph in Figure 4 illustrates that these differences in explanatory power are economically large. Table 8 also shows that the level of Life2, and the sensitivity to Q for Life2 and Life3 firms, are most important in the cross section.

[Insert Table 8 Here]

We next run the same analysis for R&D instead of CAPX in Table 9. Once again, the results are quite different for the basic and the conditional model. Both have an adjusted R^2 that is increasing over time, indicating the growing importance of innovation spending. However, the conditional model has an adjusted R^2 that is roughly twice as large (annual R^2 differences are statistically significant at the 1% level in each year). The lower graph in Figure 4 illustrates this increase in explanatory power over time. The coefficients in Table 9 indicate, not surprisingly, that firms in Life1 doing product innovation invest substantially more in R&D, especially when their Tobin's Q is high.

[Insert Figure 4 and Table 9 Here]

We next run the same analysis for the propensity to be an acquirer in Table 10. Although differences in adjusted R^2 are a tad less striking, the differences are still statistically significant at the 1% level and the conditional model yields numerous insights. For example, firms with the most mature products (life3) have the highest acquisition responsiveness to Tobin's Q. This is consistent with our earlier results regarding the product life cycle investment ordering 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 10 Here**]

In Table 11, we examine the propensity to sell assets. The explanatory power of the conditional model is higher, and the improved explanatory power is significant at the 1% level. 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 11 Here**]

Several researchers have postulated that a firm's product market structure moderates the relation between its investment expenditures and Q. The intuition underlying these arguments is that firms in concentrated markets restrict output, and investment, in order to increase their present and future cash flows (e.g., Grullon, Larkin, and Michaely (2016) and Gutierrez and Philippon (2017)). As a result, firms might optimally have high Q and low investment, so that the expected relation between investment and Q will break down in those markets. If there is an increase over time in market concentration we would expect to see a progressive reduction in the explanatory power of this relationship.

We next investigate whether the explanatory power of the conditional model is related to industry concentration. In Figure 5 we plot of the R^2 of the annual cross sectional regressions using the conditional model as shown in Tables 8 and 9. The upper figure displays results for the CAPX-Q model and the lower figure displays results for the R&D-Q model. Dynamism is defined as $(1 - life3)$ and competition is defined as the TNIC HHI from Hoberg and Phillips (2016). In each year, we perform independent sorts of the full sample into above and below median values of both dynamism and TNIC HHI. Since dynamism and HHIs are less than 5% correlated, the four subsamples are quite evenly balanced in terms of number of observations.

The highest explanatory power for both the CAPX-Q and the R&D models is in the Dynamic & Competitive subsample. The other three subsamples exhibit roughly comparable explanatory power, with Static & Concentrated having the lowest explanatory power. Visually, the separation across the groups indicates that both life cycles and competition matter, and each brings unique shifts explanatory power to the these models. Thus, accounting for both product life cycles and competition is key in understanding Q-model explanatory power. We conclude that the relationship between Tobin's Q and investment is very rich, and basic models from the literature miss most of the inferences we report for various forms of investment and Q-sensitivities.

7.1 Dynamism and the increase in Q-Model R^2

In this section, we further explore the hypothesis that increased dynamism among firms in our sample can explain the increasing R^2 results noted above, and provide evidence that increasing dynamism is related to several major trends in the operation of corporations. Specifically, to gain intuition about changes in dynamism we examine whether some of the increases in dynamism we report are associated with contemporaneous trends in corporate organization. We focus on automation, supply chain optimization, outsourcing, off-shoring, and competition to reduce labor costs.[17] We do not claim causality but instead argue that these trends are good indicators of significant operational and organizational innovations in the firm's sector. We examine the link between observed dynamism and each firm's exposure to these trends and obtain for each firm a predicted dynamism score using a fitted model. We show that the increased explanatory power of the conditional model can be explained by increasing levels of predicted dynamism over our sample period.

[17] For a discussion of offshoring and outsourcing see, for example, Mudambi and Venzin (2010), for digital technologies Evans and Wurster (2019), and Chen and Srinivassan (2019).

We expect that outsourcing and offshoring should be negatively related to firm dynamism since they remove process tasks from the corporation, leaving the corporation more static by nature. In contrast, product automation, supply-chain optimization, and reduction of labor costs are likely to facilitate increased dynamism. We measure the extent to which these issues impact each firm using textual analysis of firm 10-Ks, and develop broad sectoral measures of these activities by averaging firm exposures to each trend over each focal firm's distant peers. Distant peers are the TNIC-2 peers of the given focal firm that are not among the nearest TNIC-3 peers, where TNIC industries are defined as in Hoberg and Phillips (2016). The use of distant peers to identify firm exposures to sectoral trends ensures that we only capture exposure to these broad stylized trends and not the direct experiences of a focal firm.

We thus average the following variables over each focal firm's distant peers:

Labor competition: is the number of paragraphs in a firm's 10-K that contain the word "competition" and at least one word from the following list {labor, employee*, wage*}, all divided by the total number of paragraphs.

Outsourcing: is the number of paragraphs that contain the word "outsourc*" divided by the total number of paragraphs.

Offshoring: is the number of paragraphs mentioning the offshoring of the inputs to production to countries around the world, as defined in Hoberg and Moon (2017), all divided by the total number of paragraphs.

Supply chain focus: is the number of paragraphs that contain the phrase "supply chain," divided by the total number of paragraphs.

Production automation: is the number of paragraphs that contain the word root "automat" and either "production" or "manufactur*", divided by the total number of paragraphs.

To ensure that these discussions focus on production rather than product offerings, we exclude the Item 1 of the 10-K from the above queries. For each focal firm, we then regress dynamism on these sectoral trend variables along with a control for firm size and firm fixed effects. We then define "Predicted dynamism" as the predicted values from this regression. The results of this first stage regression are displayed in Table 12. We present results for our entire sample, and separately for large and small firms.

[Insert Table 12 Here]

Row (1) of Table 12 shows that firms with greater exposure to sectoral labor competition, automated production, and focus on the supply chain became more dynamic. Also as expected, firms exposed to outsourcing and offshoring reduced their dynamism as these firms became less involved in production of their own goods (making them more static by definition). Row (2) illustrates that many results are more salient for larger firms. This is consistent with the broader finding in our study that increases in firm dynamism are stronger for larger firms (see Figure 2).

We use "predicted dynamism" to explore whether firms that are more dynamic for plausibly exogenous reasons have policies that are better-explained by investment-Q models. Figure 6 provides a visual test of this prediction. The upper panel plots the R^2 for the CAPX-Q model (see Table 8) separately for firms with above and below median levels of predicted dynamism. Consistent with our hypothesis, the figure shows that the increase in R^2 for the CAPX-Q model is almost fully explained by firms with higher levels of predicted dynamism. We find similar and perhaps sharper results for the R&D-Q model in the lower panel of Figure 6.

[Insert Figure 6 Here]

Table 13 formalizes the visual evidence in Figure 6. In Panel A, we regress the annual R^2 results from Figure 6 on a time trend. Rows (1) to (3) display results for the CAPX-Q model and show that the time trend is significant at the 1% level for above-median dynamism firms, and is very close to zero for low dynamism firms. The results are even more striking for the R&D-Q model in rows (4) to (6). The time trend for high dynamism firms is significantly with a t-statistic of 9.19, which compares to a trend for low dynamism firms that is barely significant at the 10% level. The economic magnitude of the time trend is more than 4x larger for above-median dynamism firms.

[Insert Table 13 Here]

To establish robustness, Panel B of Table 13 tests the same hypothesis using a random sampling approach. Separately for each year, we randomly draw 1000 samples, each having 250 observations. We then reestimate the Q-model in Table 8 (CAPX-Q model) and Table 9 (R&D-Q model) for each of the 1000 samples. We store the R^2 from these regressions and we compute the average predicted dynamism of each sample. This process generates a database of 20,000 observations containing Q-model R^2 and predicted dynamism over our 20 year sample. Finally, we use this database to regress the R^2 of each Q model on the average predicted dynamism of the sample it came from, controlling for year fixed effects. Rows (7) and (9) show that R^2 is significantly higher in samples with higher levels of predicted dynamism. Rows (8) and (10) further show that the relationship between dynamism and R^2 is increasing over time for both CAPX and R&D. The tests in Panel C are analogous to those in Panel B except we use raw dynamism instead of predicted dynamism.

We conclude that the increasing investment Q-model R^2's we reported earlier are potentially driven by increased levels of dynamism. The results regarding sectoral trends are further suggestive, and indicate that the increases in dynamism are potentially related to major stylized trends such as automation, cheap labor, and outsourcing. We believe that further research examining these trends should be fruitful to understanding corporate finance policies more broadly.

8 Conclusion

Motivated by the interaction between product life cycle and Q-theories, we develop a four-stage text-based model of the product life cycle that aggregates to the firm-level as a 4-vector of firm-level 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 text-based life cycle model using anchor-phrase technologies applied on annual firm 10-Ks, which yields a firm-year panel of exposures. This allows us to conduct rigorous tests based on within-firm variation over time, as is central to the predictions of life cycle theories.

Our first main result is evidence of a natural ordering of investment policies over the life cycle. Conditioning on the life cycle dramatically increases the R^2 of Q-models explaining investments in R&D, CAPX, acquisitions, and asset sales. Over the cycle, firms initially focus on and have high Q-sensitivities for R&D, and this gravitates toward CAPX as firms shift from product to process innovation. Later in the cycle, firms shift from organic to inorganic investment in the form of acquisitions, and then to asset sales as firms enter decline. Numerous novel additional results emerge such as: (1) mature firms have negative R&D sensitivity to Q indicating R&D is symptomatic of negative states of the world and competitive threats for these mature firms, and (2) some firms entering decline are able to escape delisting as they shift toward acquisitions when valuations rise and sustainable growth opportunities re-emerge. These results are all novel to the literature as none of these inferences obtain using low dimensional representations of the life cycle such as firm age.

Our results broadly support our theoretical framework rooted in the confluence of life cycle and Q-theories. They also establish new results regarding how recessionary shocks can accelerate firm progressions toward later stages of the life cycle, indicating deeper ramifications of recessions that are likely to persist. We also observe a new structural trend among larger firms away from the static mature life cycle stage and toward more dynamic life cycle stages. This trend helps to explain an economically large increasing ability of our new life cycle conditional Q-model to explain R&D and CAPX over time. This trend appears to be related, at least in part, to sectoral changes in operational practices such as automation and outsourcing that have received a great deal of attention in the media. We believe that the implications of our study are broad, and understanding the role of product life cycles in a wide array of corporate policies and outcomes in finance, economics, and across business disciplines, is likely to be fruitful.

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Table 1: Summary Statistics

Summary statistics are reported for our sample of 68,899 observations based on annual firm observations from 1998 to 2017. 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	0.242	0.135	0.000	0.223	1.000	68,899
life2	0.417	0.174	0.000	0.398	1.000	68,899
life3	0.274	0.128	0.000	0.264	1.000	68,899
life4	0.067	0.086	0.000	0.032	0.631	68,899
lifedelist	0.027	0.163	0.000	0.000	1.000	68,899
		Panel B: Investment and Tobin's Q				
R&D/Assets	0.059	0.117	0.000	0.000	1.020	68,899
CAPX/Assets	0.061	0.080	-0.000	0.036	0.989	68,899
SDC Acquirer Dummy	0.340	0.474	0.000	0.000	1.000	68,899
SDC Target Dummy	0.189	0.392	0.000	0.000	1.000	68,899
Tobin's Q	1.860	1.993	0.200	1.252	35.487	68,899

Table 2: Pearson Correlation Coefficients

Pearson Correlation Coefficients (Panel A) and autoregressive coefficients (Panel B) are reported for our sample of 68,899 observations based on annual firm observations from 1998 to 2017. 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	R&D/ Assets	CAPX/ Assets	SDC Acquirer	SDC Target	Tobin's Q	Log Age
Panel A: Correlation Coefficients										
life2	-0.649									
life3	-0.006	-0.601								
life4	-0.249	-0.115	-0.252							
R&D/Assets	0.553	-0.330	-0.079	-0.083						
CAPX/Assets	-0.149	0.273	-0.135	-0.118	-0.094					
SDC Acquirer	-0.034	-0.052	0.119	-0.018	-0.088	0.035				
SDC Target	-0.108	0.001	-0.011	0.182	-0.088	-0.008	0.176			
Tobin's Q	0.328	-0.202	0.008	-0.119	0.397	0.114	0.024	-0.081		
Log Firm Age	-0.224	0.098	0.001	0.153	-0.201	-0.094	0.067	0.164	-0.205	
Log Assets	-0.247	0.149	0.029	0.044	-0.305	0.026	0.265	0.276	-0.166	0.391

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 1998 to 2017. 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	Tobin's Q	10-K Size	Adj R^2	Obs.
				Panel A: Firm and Year Fixed Effects			
(1)	life1	–0.007				0.80	68,965
		(–1.88)					
(2)	life2	–0.065				0.77	68,965
		(–11.75)					
(3)	life3	0.057				0.65	68,965
		(11.37)					
(4)	life4	0.015				0.41	68,965
		(4.38)					
(5)	lifedelist	0.049				0.31	68,965
		(16.28)					
				Panel B: Firm and Year Fixed Effects Plus Controls			
(6)	life1	–0.008	0.004	0.003	0.000	0.80	68,899
		(–1.99)	(3.90)	(10.90)	(–12.91)		
(7)	life2	–0.062	–0.006	–0.002	0.000	0.77	68,899
		(–11.35)	(–3.84)	(–4.61)	(11.17)		
(8)	life3	0.051	0.009	0.000	0.000	0.65	68,899
		(10.49)	(6.75)	(0.22)	(–11.53)		
(9)	life4	0.018	–0.007	–0.001	0.000	0.42	68,899
		(5.25)	(–6.64)	(–6.45)	(11.67)		
(10)	lifedelist	0.053	–0.021	–0.003	0.000	0.31	68,899
		(16.40)	(–13.89)	(–7.42)	(4.43)		

Table 4: Tech Bust and Financial Crisis and Life Cycle Transitions

The table reports Difference-in-Difference OLS estimates and economic magnitudes for three shock periods. We consider the two NBER recessions. In Panel A, we compare the technology bust NBER recession in 2001 to the three year period prior (1998 to 2000). In Panel B, we compare the financial crisis NBER recession from 2008 to 2009 to the prior three year period (2004 to 2006). Although it does not materially impact our results, we omit 2007 for this shock as this NBER recession officially began at the very end of 2007 in December making it ambiguous. In all regressions, one observation is one firm in one year. The key RHS variables are four dummies indicating the ex-ante life stage of the firm (and their interactions with the post-treatment dummy). To determine the binary life stage of a given firm, we first de-mean the four life stages. A firm is deemed to be in life1 if its demeaned life1 is larger than its de-meaned values of the other three stages. We perform a similar calculation for the other three stages. The dependent variable is a dummy indicating the ex-post change in the life cycle stage. To compute this dummy variable, we first compute the ex-post change in the four life cycle stages for each firm. If the change in life1 is more positive than the change in the other four stages, the dummy (Toward Life1) is set to one. We compute similar change variables for the other three stages. The table below depicts the results of regressions of these ex-post change dummies on the four ex-ante life stage dummies and interactions of these variables with the post-treatment dummy for each difference-in-difference test. We additionally include controls for logassets, log age, and Fama-French-48 industry fixed effects. To conserve space, we only report the coefficients and the t-statistics for the important post-treatment x initial life cycle stage variables. All standard errors are clustered by firm. In the last four columns, we display economic magnitudes based on a transition matrix interpretation of the same regressions. In particular, we report the difference (post-treatment minus pre-treatment) changes in transition probabilities from the ex-ante life cycle stages (noted in the column headers) toward the ex post stages noted in the first column "Transition". For example, the figure in the fourth row first column of 0.082 indicates that the probability that a life1 firm moves toward life4 is 8.2 percentage points higher during the tech bust recession than it was during the prior three-year pre-treatment period.

		Treatment Regression Coefficients				Treatment Regression t-statistics					Change in Transition Matrix Probabilities				
	Dep. Variable	Life1	Life2	Life3	Life4	Life1	Life2	Life3	Life4	R^2	Transition	Life1	Life2	Life3	Life4
	Panel A: Compare 1998 to 2000 (pre-treatment) to 2001 (tech bust NBER recession)														
1	Toward Life1	-0.061	-0.073	-0.093	-0.075	-4.64	-4.45	-6.14	-3.25	0.293	Toward Life1	-0.063	-0.074	-0.094	-0.072
2	Toward Life2	0.028	-0.037	0.040	0.039	1.87	-2.24	2.44	1.53	0.298	Toward Life2	0.064	-0.001	0.078	0.073
3	Toward Life3	-0.040	-0.009	0.007	0.022	-2.64	-0.52	0.51	0.86	0.341	Toward Life3	-0.084	-0.052	-0.038	-0.024
4	Toward Life4	0.073	0.118	0.046	0.014	6.64	8.66	3.99	0.69	0.130	Toward Life4	0.082	0.127	0.054	0.022
	Panel B: Compare 2004 to 2006 (pre-treatment) to 2008 to 2009 (fin crisis NBER recession)														
5	Toward Life1	0.022	-0.055	0.027	-0.024	1.33	-3.64	1.53	-1.32	0.293	Toward Life1	0.024	-0.055	0.028	-0.027
6	Toward Life2	-0.038	0.065	-0.043	0.049	-2.28	4.30	-2.42	2.65	0.317	Toward Life2	-0.097	0.011	-0.104	-0.005
7	Toward Life3	0.035	0.014	0.028	0.006	2.00	0.93	1.67	0.34	0.317	Toward Life3	0.079	0.057	0.079	0.050
8	Toward Life4	-0.019	-0.024	-0.013	-0.032	-1.69	-2.16	-1.06	-2.33	0.123	Toward Life4	-0.007	-0.013	-0.003	-0.018

Table 5: Investment Panel Data Regressions

The table reports results from firm-year panel data OLS investment-Q regressions from 1998 to 2017. The dependent variable is ex post R&D/assets (Panel A), CAPX/Assets (Panel B), SDC Acquisitions (Panel C), and SDC Targets (Panel D). The key RHS variable in these "OLS" panel data regressions are the lagged life cycle variables and their interactions with Tobins' Q. All regressions include controls for size, age, firm fixed effects and year fixed effects. All RHS variables are ex ante measurable and are observable in year $t-1$. In each panel, we consider three subsamples: the full sample, and those with above or below median competition levels as measured using the TNIC HHI (see Hoberg and Phillips 2016). 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. In the adjusted R^2 column, we also include likelihood ratio tests examining if the conditional model's R^2 is significantly larger than that of the basic model, and all results are significant at the 1% level as indicated by the three stars. 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/ LR test	# Obs
								Panel A: R&D/Assets							
(1)	Full Sample	0.007	-0.029	0.007	0.041	0.004	0.000	0.029	-0.001	-0.013	0.012	-0.029	0.006	0.82	68,899
		(14.31)	(-21.19)	(2.60)	(5.74)	(1.05)	(0.06)	(11.26)	(-0.62)	(-4.26)	(1.59)	(-21.66)	(2.27)	1519***	
(2)	Concen. Firms	0.005	-0.017	0.006	0.024	0.002	0.002	0.018	-0.001	-0.005	0.010	-0.017	0.006	0.84	34,306
		(5.42)	(-12.30)	(2.41)	(3.77)	(0.66)	(0.25)	(4.17)	(-0.39)	(-1.60)	(1.22)	(-12.41)	(2.30)	351***	
(3)	Comp Firms	0.008	-0.039	0.008	0.060	0.006	0.006	0.032	0.000	-0.017	0.023	-0.039	0.006	0.82	34,293
		(12.19)	(-18.06)	(1.78)	(4.45)	(0.86)	(0.49)	(9.07)	(-0.17)	(-3.84)	(1.77)	(-18.52)	(1.41)	911***	
								Panel B: CAPX/Assets							
(4)	Full Sample	0.007	-0.012	-0.020	0.022	0.002	-0.025	-0.007	0.024	0.007	0.008	-0.012	-0.019	0.58	68,899
		(21.14)	(-14.89)	(-8.36)	(3.85)	(0.37)	(-4.60)	(-4.13)	(13.34)	(3.46)	(2.02)	(-15.09)	(-7.83)	1106***	
(5)	Concen. Firms	0.008	-0.013	-0.016	0.007	-0.008	-0.025	-0.004	0.016	0.009	0.010	-0.013	-0.016	0.54	34,306
		(12.92)	(-11.21)	(-4.70)	(1.03)	(-1.58)	(-3.76)	(-1.32)	(6.51)	(3.32)	(1.94)	(-11.39)	(-4.69)	244***	
(6)	Comp Firms	0.007	-0.012	-0.023	0.038	0.012	-0.023	-0.010	0.030	0.007	0.011	-0.012	-0.021	0.60	34,293
		(15.45)	(-9.37)	(-6.15)	(3.75)	(1.42)	(-2.52)	(-4.17)	(11.70)	(2.44)	(1.83)	(-9.42)	(-5.38)	849***	
								Panel C: SDC Acquisition Dummy							
(7)	Full Sample	0.016	0.010	-0.015	0.050	-0.027	-0.211	-0.030	0.038	0.049	0.049	0.007	-0.011	0.27	68,899
		(12.64)	(2.37)	(-1.06)	(1.29)	(-0.93)	(-5.67)	(-5.35)	(6.30)	(6.74)	(3.11)	(1.70)	(-0.75)	197***	
(8)	Concen. Firms	0.022	-0.003	-0.015	0.019	-0.043	-0.159	-0.032	0.041	0.052	0.057	-0.005	-0.014	0.27	34,306
		(8.14)	(-0.37)	(-0.69)	(0.36)	(-1.10)	(-3.23)	(-2.70)	(3.83)	(3.61)	(2.66)	(-0.75)	(-0.63)	68***	
(9)	Comp Firms	0.014	0.018	-0.002	0.075	-0.015	-0.273	-0.027	0.035	0.044	0.052	0.015	0.004	0.27	34,293
		(8.51)	(2.69)	(-0.11)	(1.18)	(-0.30)	(-4.29)	(-3.70)	(4.20)	(4.87)	(1.95)	(2.26)	(0.18)	113***	
								Panel D: SDC Target Dummy							
(10)	Full Sample	-0.005	0.038	0.065	-0.026	-0.008	0.062	0.005	-0.011	-0.004	-0.060	0.039	0.064	0.20	68,899
		(-5.35)	(10.98)	(5.87)	(-0.76)	(-0.31)	(1.89)	(1.16)	(-2.39)	(-0.77)	(-4.44)	(11.19)	(5.71)	51***	
(11)	Concen. Firms	-0.009	0.034	0.068	-0.022	0.008	0.021	0.006	-0.020	-0.001	-0.076	0.035	0.070	0.19	34,306
		(-4.89)	(6.21)	(3.98)	(-0.47)	(0.25)	(0.48)	(0.68)	(-2.39)	(-0.12)	(-3.30)	(6.32)	(4.05)	32***	
(12)	Comp Firms	-0.003	0.040	0.072	-0.022	-0.011	0.092	0.004	-0.001	-0.008	-0.048	0.040	0.071	0.22	34,293
		(-2.10)	(7.97)	(4.22)	(-0.40)	(-0.26)	(1.61)	(0.74)	(-0.20)	(-1.00)	(-2.14)	(8.09)	(4.08)	20***	

Table 6: Economic Magnitudes

The table reports economic magnitudes of the relationship between the life cycle variables and investment policies, and the sensitivity of these policies to Tobin's Q. The first two columns report the investment policy being analyzed, 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 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	Mean Dep. Var	High Life1 Firms	High Life2 Firms	High Life3 Firms	High Life4 Firms	All Firms
			Investment Q-Sensitivities and Life Cycle Variables				
1	R&D/Assets	0.059	0.172	0.009	0.061	0.075	0.110
2	CAPX/Assets	0.061	0.021	0.076	0.025	0.024	0.025
3	SDC Acq	0.340	0.034	0.100	0.186	0.102	0.090
4	SDC Target	0.189	-0.075	-0.066	-0.052	-0.096	-0.095

Table 7: Investment Panel Data Regressions (Age-Based Life Cycle)

The table reports results from firm-year panel data investment-Q regressions from 1998 to 2017. The dependent variable is ex post R&D/assets (Panels A), CAPX/Assets (Panel B), SDC Acquisitions (Panel C), and SDC Targets (Panel D). All dependent variables are based on the focal firm's investment policies. 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 Tobin's Q, and size controls. The life cycle variables Life1 to Life4 are dummies identifying which quartile the firm's age is in, where quartiles are formed based on yearly sorts of firm age. Life1 indicates the youngest firms and Life4 the oldest firms. 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 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.

Row	Life1	Life2	Life4	TobQ x Life1	TobQ x Life2	TobQ x Life3	TobQ x Life4	Log Assets	Adj R^2	# Obs
					Panel A: R&D/Assets					
(1)	0.002	–0.002	–0.004	0.007	0.008	0.008	0.003	–0.028	0.82	68,899
	(0.72)	(–0.92)	(–1.33)	(10.18)	(8.10)	(7.67)	(3.01)	(–21.12)		
					Panel B: CAPX/Assets					
(2)	0.009	0.003	–0.002	0.006	0.008	0.007	0.012	–0.012	0.57	68,899
	(4.01)	(1.84)	(–0.63)	(14.67)	(14.57)	(11.80)	(10.68)	(–15.31)		
					Panel C: SDC Acquisition Dummy					
(3)	0.011	0.003	–0.022	0.013	0.021	0.019	0.032	0.010	0.26	68,899
	(0.71)	(0.28)	(–1.01)	(7.67)	(8.44)	(6.99)	(5.36)	(2.25)		
					Panel D: SDC Target Dummy					
(4)	–0.032	–0.008	0.009	–0.003	–0.011	–0.005	–0.022	0.039	0.20	68,899
	(–2.44)	(–0.76)	(0.52)	(–2.44)	(–5.94)	(–2.84)	(–4.00)	(11.48)		

Table 8: CAPX Investment-Q Regressions

The table reports results from annual OLS investment-Q regressions from 1998 to 2017. 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 Tobin's 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 Tobin's 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	Tobin's 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	0.004	-0.021	0.005	0.018	-0.055	0.166	N/A	-0.001	-0.012	0.027	0.019	0.007	0.113
	(2.84)	(-5.85)	(3.72)		(-2.63)	(10.1)		(-0.03)	(-1.94)	(4.75)	(2.52)	(0.31)	
(2) 1999	0.004	-0.007	0.004	0.012	-0.033	0.088	N/A	-0.085	-0.001	-0.000	0.023	0.010	0.081
	(3.81)	(-2.95)	(3.69)		(-2.17)	(7.11)		(-3.51)	(-0.18)	(-0.06)	(4.57)	(0.60)	
(3) 2000	0.004	-0.003	0.000	0.020	-0.020	0.142	N/A	-0.070	-0.007	0.017	0.013	0.014	0.114
	(6.54)	(-1.01)	(0.22)		(-1.13)	(10.2)		(-2.71)	(-2.24)	(4.42)	(3.26)	(2.21)	
(4) 2001	0.003	0.002	0.002	0.010	-0.020	0.132	N/A	-0.076	-0.011	0.025	0.018	-0.026	0.142
	(4.49)	(0.74)	(2.04)		(-1.29)	(11.3)		(-3.54)	(-3.75)	(6.77)	(4.26)	(-2.48)	
(5) 2002	0.005	0.004	0.002	0.018	-0.011	0.103	N/A	-0.026	-0.004	0.015	0.014	0.014	0.128
	(5.62)	(1.71)	(2.51)		(-0.79)	(10.3)		(-1.41)	(-1.08)	(4.16)	(2.69)	(1.16)	
(6) 2003	0.007	0.001	0.002	0.018	-0.001	0.127	N/A	-0.043	-0.001	0.019	0.012	0.007	0.143
	(5.80)	(0.27)	(2.64)		(-0.09)	(10.9)		(-2.32)	(-0.21)	(4.14)	(1.94)	(0.54)	
(7) 2004	0.002	-0.003	0.001	0.002	-0.018	0.141	N/A	-0.024	-0.008	0.009	0.019	0.021	0.148
	(2.30)	(-1.11)	(0.92)		(-1.12)	(10.8)		(-1.11)	(-2.02)	(2.39)	(3.29)	(1.70)	
(8) 2005	0.002	-0.004	0.002	0.002	-0.016	0.209	N/A	-0.014	-0.020	0.025	0.012	0.019	0.215
	(1.40)	(-1.32)	(2.01)		(-0.83)	(13.4)		(-0.55)	(-3.73)	(5.69)	(1.54)	(1.26)	
(9) 2006	0.003	-0.014	0.004	0.010	0.013	0.293	N/A	0.028	-0.029	0.052	-0.018	0.027	0.254
	(1.94)	(-3.50)	(2.87)		(0.55)	(15.2)		(0.87)	(-4.63)	(9.09)	(-1.81)	(1.16)	
(10) 2007	0.001	-0.022	0.007	0.021	0.016	0.345	N/A	0.042	-0.004	0.027	-0.014	0.003	0.265
	(0.44)	(-5.26)	(4.66)		(0.60)	(15.9)		(1.16)	(-0.51)	(4.30)	(-1.22)	(0.13)	
(11) 2008	0.002	-0.016	0.009	0.023	0.038	0.339	N/A	0.034	-0.016	0.025	0.005	0.038	0.282
	(1.15)	(-4.05)	(5.90)		(1.44)	(16.3)		(1.05)	(-2.76)	(4.65)	(0.52)	(1.72)	
(12) 2009	0.002	-0.005	0.005	0.025	0.002	0.153	N/A	-0.007	-0.011	0.025	0.004	-0.013	0.212
	(1.53)	(-2.26)	(6.56)		(0.11)	(12.5)		(-0.37)	(-2.06)	(4.63)	(0.42)	(-0.75)	
(13) 2010	0.008	-0.012	0.008	0.040	0.032	0.240	N/A	0.030	-0.025	0.052	-0.001	-0.010	0.298
	(4.55)	(-3.60)	(7.06)		(1.51)	(14.9)		(1.20)	(-4.05)	(9.36)	(-0.13)	(-0.48)	
(14) 2011	0.002	-0.014	0.007	0.022	0.023	0.263	N/A	0.026	-0.016	0.029	0.007	-0.001	0.258
	(1.20)	(-3.81)	(5.28)		(0.90)	(13.8)		(0.88)	(-2.53)	(4.95)	(0.68)	(-0.05)	
(15) 2012	0.003	-0.021	0.007	0.027	0.015	0.287	N/A	0.052	-0.024	0.040	0.005	0.003	0.268
	(1.39)	(-5.41)	(4.69)		(0.53)	(13.2)		(1.44)	(-3.00)	(5.62)	(0.36)	(0.11)	
(16) 2013	0.001	-0.018	0.006	0.026	0.014	0.248	N/A	0.030	-0.017	0.021	0.021	-0.002	0.260
	(0.73)	(-5.37)	(4.63)		(0.53)	(12.8)		(0.95)	(-2.67)	(3.46)	(1.89)	(-0.09)	
(17) 2014	-0.003	-0.022	0.005	0.023	0.037	0.326	N/A	0.111	-0.016	0.020	0.009	0.005	0.235
	(-1.64)	(-5.39)	(3.35)		(1.07)	(12.9)		(2.61)	(-2.27)	(3.21)	(0.69)	(0.18)	
(18) 2015	0.001	-0.011	0.004	0.025	-0.025	0.146	N/A	0.001	-0.013	0.021	0.015	-0.025	0.190
	(1.16)	(-4.69)	(5.13)		(-1.19)	(9.26)		(0.02)	(-2.95)	(4.59)	(1.94)	(-1.35)	
(19) 2016	0.001	-0.005	0.002	0.004	-0.015	0.126	N/A	0.004	-0.016	0.019	0.005	0.019	0.145
	(0.61)	(-2.09)	(2.63)		(-0.70)	(8.16)		(0.16)	(-2.88)	(4.29)	(0.60)	(0.95)	
(20) 2017	0.001	-0.006	0.003	0.008	0.008	0.192	N/A	0.026	-0.011	0.033	-0.019	0.007	0.192
	(0.80)	(-2.27)	(3.34)		(0.35)	(10.8)		(0.86)	(-1.91)	(5.80)	(-1.89)	(0.29)	

Table 9: R&D Investment-Q Regressions

The table reports results from annual OLS investment-Q regressions from 1998 to 2017. 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 Tobin's 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 Tobin's 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	Tobin's 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	0.022	-0.002	-0.011	0.180	0.256	0.000	N/A	0.039	0.063	-0.002	-0.026	0.014	0.349
	(18.8)	(-0.79)	(-9.71)		(16.9)	(0.04)		(1.62)	(13.8)	(-0.52)	(-4.86)	(0.90)	
(2) 1999	0.027	-0.002	-0.013	0.221	0.356	0.041	N/A	0.115	0.092	-0.002	-0.068	0.042	0.444
	(21.6)	(-0.73)	(-10.0)		(20.2)	(2.83)		(4.08)	(20.8)	(-0.50)	(-11.5)	(2.08)	
(3) 2000	0.019	0.004	-0.015	0.266	0.345	0.036	N/A	0.113	0.070	-0.011	-0.043	0.018	0.448
	(23.9)	(0.98)	(-10.8)		(17.2)	(2.29)		(3.83)	(20.6)	(-2.64)	(-9.78)	(2.57)	
(4) 2001	0.016	-0.009	-0.012	0.232	0.270	0.013	N/A	0.062	0.035	-0.002	-0.016	0.009	0.410
	(20.0)	(-3.27)	(-11.5)		(17.6)	(1.14)		(2.90)	(12.0)	(-0.57)	(-3.76)	(0.85)	
(5) 2002	0.024	-0.007	-0.012	0.283	0.274	0.031	N/A	0.093	0.053	0.005	-0.037	0.048	0.451
	(22.1)	(-2.45)	(-11.9)		(16.7)	(2.55)		(4.26)	(12.9)	(1.03)	(-6.15)	(3.33)	
(6) 2003	0.031	-0.013	-0.012	0.230	0.428	0.084	N/A	0.132	0.104	-0.011	-0.059	0.019	0.541
	(17.6)	(-3.35)	(-9.92)		(24.2)	(5.94)		(5.82)	(18.4)	(-1.90)	(-7.64)	(1.24)	
(7) 2004	0.027	-0.005	-0.011	0.260	0.385	0.063	N/A	0.101	0.087	-0.009	-0.049	0.005	0.518
	(18.9)	(-1.34)	(-8.49)		(20.0)	(4.12)		(4.02)	(17.5)	(-2.02)	(-7.06)	(0.36)	
(8) 2005	0.024	-0.013	-0.009	0.217	0.465	0.117	N/A	0.139	0.096	-0.005	-0.075	-0.006	0.557
	(15.8)	(-3.35)	(-6.80)		(24.3)	(7.66)		(5.62)	(18.5)	(-1.10)	(-10.0)	(-0.38)	
(9) 2006	0.028	-0.013	-0.010	0.220	0.518	0.120	N/A	0.129	0.086	-0.015	-0.038	-0.007	0.540
	(16.0)	(-3.03)	(-6.99)		(23.7)	(6.85)		(4.42)	(15.0)	(-2.90)	(-4.24)	(-0.33)	
(10) 2007	0.028	-0.007	-0.014	0.207	0.619	0.161	N/A	0.191	0.096	-0.014	-0.056	0.009	0.529
	(13.9)	(-1.47)	(-8.39)		(23.8)	(7.63)		(5.48)	(14.1)	(-2.38)	(-5.21)	(0.36)	
(11) 2008	0.030	-0.006	-0.015	0.246	0.630	0.178	N/A	0.210	0.087	-0.006	-0.061	0.012	0.570
	(16.2)	(-1.41)	(-9.18)		(24.9)	(8.84)		(6.73)	(15.2)	(-1.10)	(-6.00)	(0.54)	
(12) 2009	0.036	-0.006	-0.018	0.213	0.601	0.168	N/A	0.181	0.107	-0.011	-0.069	0.031	0.509
	(12.7)	(-1.41)	(-11.8)		(22.4)	(8.12)		(5.96)	(11.4)	(-1.19)	(-4.18)	(1.05)	
(13) 2010	0.041	-0.001	-0.013	0.312	0.440	0.116	N/A	0.155	0.138	0.003	-0.110	0.054	0.601
	(19.5)	(-0.20)	(-9.86)		(18.9)	(6.63)		(5.72)	(20.8)	(0.46)	(-9.27)	(2.43)	
(14) 2011	0.036	-0.002	-0.014	0.315	0.510	0.146	N/A	0.156	0.106	0.003	-0.079	-0.003	0.608
	(18.7)	(-0.53)	(-10.2)		(21.1)	(8.19)		(5.58)	(18.0)	(0.55)	(-7.81)	(-0.15)	
(15) 2012	0.028	-0.010	-0.014	0.224	0.575	0.167	N/A	0.201	0.088	0.003	-0.083	0.025	0.546
	(13.2)	(-2.45)	(-9.49)		(22.3)	(8.63)		(6.21)	(12.3)	(0.51)	(-6.63)	(0.92)	
(16) 2013	0.031	-0.001	-0.012	0.273	0.458	0.112	N/A	0.107	0.102	-0.015	-0.046	-0.025	0.572
	(17.4)	(-0.21)	(-9.09)		(18.5)	(6.19)		(3.63)	(17.0)	(-2.53)	(-4.38)	(-1.10)	
(17) 2014	0.029	-0.003	-0.011	0.318	0.457	0.111	N/A	0.122	0.106	-0.011	-0.069	-0.021	0.650
	(19.8)	(-0.82)	(-8.76)		(19.4)	(6.46)		(4.22)	(22.2)	(-2.50)	(-8.12)	(-1.05)	
(18) 2015	0.031	-0.007	-0.012	0.294	0.463	0.096	N/A	0.087	0.107	-0.013	-0.057	-0.025	0.583
	(18.2)	(-2.04)	(-8.83)		(16.7)	(4.60)		(2.59)	(18.4)	(-2.15)	(-5.52)	(-1.02)	
(19) 2016	0.029	-0.009	-0.009	0.284	0.395	0.078	N/A	0.056	0.118	-0.010	-0.061	-0.062	0.601
	(18.5)	(-2.95)	(-7.68)		(16.5)	(4.71)		(2.12)	(19.9)	(-1.98)	(-6.24)	(-2.85)	
(20) 2017	0.035	-0.031	-0.014	0.283	0.625	0.134	N/A	0.112	0.099	-0.016	-0.014	-0.081	0.586
	(14.8)	(-7.01)	(-8.37)		(19.4)	(5.42)		(2.70)	(12.7)	(-2.06)	(-1.00)	(-2.39)	

Table 10: SDC Acquisition Investment-Q Regressions

The table reports results from annual OLS investment-Q regressions from 1998 to 2017. 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 Tobin's 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 Tobin's 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	Tobin's 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	0.035	-0.024	0.082	0.097	0.007	-0.230	N/A	0.032	-0.066	0.100	0.054	-0.042	0.107
	(4.32)	(-1.87)	(15.0)		(0.08)	(-3.55)		(0.26)	(-1.44)	(3.23)	(1.40)	(-0.35)	
(2) 1999	0.040	0.018	0.073	0.095	0.042	-0.185	N/A	0.083	0.007	0.059	-0.005	0.441	0.102
	(4.77)	(1.30)	(13.0)		(0.47)	(-2.66)		(0.63)	(0.16)	(2.15)	(-0.15)	(3.08)	
(3) 2000	0.025	0.023	0.075	0.108	0.156	-0.123	N/A	-0.181	-0.057	0.053	0.081	-0.013	0.115
	(4.61)	(1.68)	(13.7)		(1.67)	(-1.77)		(-1.43)	(-1.81)	(2.13)	(2.54)	(-0.19)	
(4) 2001	0.035	0.013	0.074	0.115	0.093	-0.232	N/A	-0.143	-0.032	0.059	0.065	0.032	0.126
	(5.51)	(0.92)	(14.1)		(1.03)	(-3.52)		(-1.17)	(-1.05)	(2.25)	(2.05)	(0.32)	
(5) 2002	0.036	0.017	0.070	0.104	0.111	-0.142	N/A	-0.045	-0.104	0.055	0.138	0.038	0.111
	(4.22)	(1.10)	(12.8)		(1.07)	(-1.98)		(-0.36)	(-2.14)	(1.84)	(2.95)	(0.34)	
(6) 2003	0.032	-0.009	0.072	0.094	-0.051	-0.275	N/A	-0.139	-0.034	-0.056	0.167	0.170	0.104
	(3.00)	(-0.53)	(12.4)		(-0.43)	(-3.32)		(-1.10)	(-0.54)	(-1.37)	(3.18)	(1.28)	
(7) 2004	0.023	0.013	0.065	0.068	-0.009	-0.376	N/A	-0.220	-0.175	0.113	0.088	-0.087	0.087
	(2.53)	(0.71)	(9.98)		(-0.06)	(-3.83)		(-1.61)	(-2.91)	(3.16)	(1.48)	(-0.81)	
(8) 2005	0.038	0.035	0.058	0.063	-0.069	-0.327	N/A	-0.161	-0.028	0.068	0.058	0.001	0.070
	(4.26)	(1.89)	(8.80)		(-0.47)	(-3.13)		(-1.13)	(-0.53)	(1.92)	(1.05)	(0.01)	
(9) 2006	0.021	-0.013	0.073	0.075	-0.413	-0.533	N/A	-0.206	0.100	0.013	-0.080	0.094	0.087
	(2.09)	(-0.69)	(10.8)		(-2.59)	(-4.80)		(-1.37)	(1.50)	(0.29)	(-1.12)	(0.81)	
(10) 2007	0.011	0.005	0.077	0.090	-0.325	-0.587	N/A	-0.189	-0.014	0.041	-0.028	0.014	0.102
	(1.13)	(0.26)	(11.5)		(-1.97)	(-4.75)		(-1.17)	(-0.22)	(0.84)	(-0.35)	(0.11)	
(11) 2008	0.026	0.023	0.085	0.117	-0.139	-0.683	N/A	-0.605	-0.012	-0.004	0.066	0.079	0.148
	(2.89)	(1.35)	(13.2)		(-0.84)	(-5.66)		(-3.85)	(-0.21)	(-0.11)	(0.98)	(0.67)	
(12) 2009	0.061	0.007	0.058	0.067	-0.003	-0.521	N/A	-0.312	-0.176	0.165	0.031	0.180	0.090
	(4.13)	(0.44)	(8.83)		(-0.02)	(-4.21)		(-2.01)	(-1.59)	(2.77)	(0.28)	(0.98)	
(13) 2010	0.011	-0.005	0.070	0.067	-0.275	-0.749	N/A	-0.702	-0.223	0.130	0.031	-0.166	0.102
	(0.73)	(-0.23)	(9.45)		(-1.45)	(-5.29)		(-3.79)	(-2.42)	(1.80)	(0.29)	(-0.82)	
(14) 2011	0.011	0.037	0.080	0.105	-0.422	-0.741	N/A	-0.448	-0.025	0.124	-0.131	-0.149	0.127
	(0.90)	(1.89)	(10.8)		(-2.15)	(-5.09)		(-2.28)	(-0.34)	(2.54)	(-1.52)	(-0.88)	
(15) 2012	0.028	0.050	0.086	0.125	-0.146	-0.420	N/A	-0.126	-0.001	-0.001	0.066	0.239	0.130
	(2.31)	(2.53)	(11.7)		(-0.75)	(-2.96)		(-0.59)	(-0.01)	(-0.03)	(0.68)	(0.97)	
(16) 2013	0.036	0.011	0.075	0.090	-0.258	-0.493	N/A	-0.432	-0.014	-0.005	0.128	0.099	0.097
	(3.20)	(0.55)	(10.2)		(-1.27)	(-3.35)		(-2.00)	(-0.16)	(-0.11)	(1.32)	(0.41)	
(17) 2014	0.033	0.004	0.082	0.099	-0.314	-0.698	N/A	-0.149	0.066	-0.007	0.080	-0.170	0.120
	(3.61)	(0.18)	(11.1)		(-1.51)	(-4.70)		(-0.69)	(0.88)	(-0.20)	(0.97)	(-0.99)	
(18) 2015	0.020	0.000	0.075	0.083	-0.031	-0.441	N/A	-0.266	0.035	-0.004	0.030	-0.063	0.090
	(1.98)	(0.03)	(10.4)		(-0.14)	(-2.84)		(-1.23)	(0.51)	(-0.09)	(0.30)	(-0.33)	

Table 11: SDC Acquisition Target-Q Regressions

The table reports results from annual OLS divestiture-Q regressions from 1998 to 2017. 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 Tobin's 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 Tobin's 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	Tobin's 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	-0.007	0.041	0.054	0.090	0.064	-0.050	N/A	-0.049	0.068	-0.033	-0.044	-0.050	0.099
	(-1.07)	(3.84)	(12.1)		(0.92)	(-0.95)		(-0.49)	(1.80)	(-1.31)	(-1.39)	(-0.52)	
(2) 1999	-0.009	0.050	0.055	0.095	0.152	-0.054	N/A	0.408	-0.076	0.004	0.006	0.238	0.103
	(-1.27)	(4.39)	(11.6)		(2.00)	(-0.93)		(3.69)	(-2.14)	(0.17)	(0.21)	(1.97)	
(3) 2000	-0.001	0.031	0.049	0.072	0.095	-0.050	N/A	0.288	-0.018	0.012	0.012	-0.081	0.083
	(-0.25)	(2.68)	(10.7)		(1.21)	(-0.86)		(2.73)	(-0.68)	(0.59)	(0.47)	(-1.38)	
(4) 2001	-0.001	0.048	0.055	0.105	0.053	-0.133	N/A	0.237	0.006	-0.018	0.000	0.032	0.117
	(-0.16)	(4.14)	(12.5)		(0.70)	(-2.41)		(2.32)	(0.24)	(-0.82)	(0.00)	(0.38)	
(5) 2002	-0.009	0.027	0.052	0.091	-0.091	-0.127	N/A	0.261	-0.029	-0.003	-0.013	0.104	0.102
	(-1.24)	(2.19)	(11.6)		(-1.07)	(-2.14)		(2.56)	(-0.73)	(-0.14)	(-0.33)	(1.15)	
(6) 2003	-0.013	0.032	0.055	0.098	-0.169	-0.152	N/A	0.067	0.094	-0.042	-0.039	-0.139	0.106
	(-1.52)	(2.38)	(11.6)		(-1.71)	(-2.23)		(0.65)	(1.83)	(-1.26)	(-0.92)	(-1.28)	
(7) 2004	-0.009	0.033	0.049	0.078	0.096	-0.016	N/A	0.435	0.015	0.025	-0.074	-0.069	0.090
	(-1.27)	(2.26)	(9.50)		(0.84)	(-0.20)		(3.97)	(0.31)	(0.87)	(-1.56)	(-0.80)	
(8) 2005	-0.012	0.041	0.052	0.086	0.046	-0.094	N/A	0.250	0.067	-0.039	-0.048	-0.060	0.096
	(-1.65)	(2.68)	(9.54)		(0.37)	(-1.09)		(2.11)	(1.55)	(-1.34)	(-1.05)	(-0.66)	
(9) 2006	-0.024	0.057	0.062	0.127	-0.142	-0.278	N/A	0.162	0.014	0.039	-0.151	-0.117	0.141
	(-2.84)	(3.78)	(11.3)		(-1.08)	(-3.06)		(1.32)	(0.26)	(1.03)	(-2.57)	(-1.23)	
(10) 2007	-0.021	0.067	0.052	0.106	0.073	-0.039	N/A	0.452	0.037	-0.064	0.019	-0.059	0.128
	(-2.75)	(4.48)	(9.44)		(0.54)	(-0.39)		(3.43)	(0.68)	(-1.59)	(0.29)	(-0.55)	
(11) 2008	-0.012	0.046	0.034	0.047	0.060	-0.137	N/A	0.300	-0.004	-0.005	0.027	-0.275	0.072
	(-1.59)	(3.23)	(6.27)		(0.44)	(-1.35)		(2.28)	(-0.09)	(-0.17)	(0.49)	(-2.78)	
(12) 2009	-0.044	0.014	0.045	0.060	0.187	-0.066	N/A	0.422	0.071	-0.015	-0.130	-0.324	0.079
	(-3.46)	(0.95)	(8.13)		(1.26)	(-0.62)		(3.19)	(0.75)	(-0.30)	(-1.39)	(-2.08)	
(13) 2010	-0.019	0.051	0.050	0.074	0.112	-0.113	N/A	0.288	-0.097	0.030	-0.055	0.179	0.092
	(-1.47)	(3.03)	(8.07)		(0.69)	(-0.93)		(1.82)	(-1.23)	(0.49)	(-0.60)	(1.03)	
(14) 2011	-0.003	0.044	0.065	0.113	0.183	0.079	N/A	0.381	-0.025	0.054	-0.031	-0.208	0.118
	(-0.33)	(2.72)	(10.8)		(1.13)	(0.66)		(2.35)	(-0.41)	(1.33)	(-0.43)	(-1.48)	
(15) 2012	-0.017	0.060	0.056	0.093	0.193	-0.081	N/A	0.164	-0.080	0.081	-0.077	-0.365	0.101
	(-1.65)	(3.56)	(8.91)		(1.17)	(-0.67)		(0.90)	(-1.16)	(2.03)	(-0.94)	(-1.74)	
(16) 2013	-0.024	0.067	0.052	0.098	0.121	0.038	N/A	0.646	-0.073	0.019	0.039	-0.450	0.122
	(-2.56)	(3.97)	(8.66)		(0.73)	(0.31)		(3.65)	(-1.07)	(0.53)	(0.49)	(-2.30)	
(17) 2014	-0.009	0.060	0.048	0.071	0.454	0.301	N/A	0.746	-0.016	0.026	-0.049	0.002	0.082
	(-1.08)	(3.44)	(7.59)		(2.53)	(2.35)		(4.02)	(-0.24)	(0.82)	(-0.68)	(0.01)	
(18) 2015	-0.005	0.050	0.058	0.094	0.118	0.032	N/A	0.695	0.046	0.037	-0.052	-0.351	0.118
	(-0.57)	(3.14)	(9.64)		(0.66)	(0.25)		(3.85)	(0.80)	(0.96)	(-0.64)	(-2.21)	

Table 12: First Stage Dynamism Regressions

The table reports results from annual OLS firm dynamism regressions from 1998 to 2017. One observation is one firm in on year. The dependent variable is the year t natural logarithm of dynamism, which is defined as $(1 - life3)$. All RHS variables are ex ante observable in year $t-1$. Variables based on peer-of-peer values (as noted in column headers) are based on the variable's average value across firms that are in the focal firm's TNIC-2 industry but that are not in the focal firm's TNIC-3 industry (and hence are distant peers, whose characteristics are more plausibly exogenous). The following variables are based on the firm's 10-K. Labor competition is the number of paragraphs that contain the word "competition" and at least one word from the following list (labor, employee*, wage*), all divided by the total number of paragraphs. Outsourcing is the number of paragraphs that contain the word "outsourc*" divided by the total number of paragraphs. Supply chain focus is the number of paragraphs that contain the phrase "supply chain," divided by the total number of paragraphs. Production automation is the number of paragraphs that contain the word root "automat" and a word from "production" or "manufactur*". These queries exclude the 10-K's Item 1 to ensure focus on production and inputs. t-statistics are in parentheses. Offshoring is based on Hoberg and Moon (2017) and is number of mentions a firm makes to purchasing inputs to production abroad divided by the total number of paragraphs. All regressions include firm and year fixed effects and are clustered by firm.

Row	Sample	Peer of Peer Labor Competition	Peer of Peer Out-sourcing	Peer of Peer Off-Shoring	Peer of Peer Supply Chain Focus	Production Automation	Log Assets	Log 10-K Size	Adj R^2	# Obs.
(1)	All Firms	5.418	–6.468	–0.083	8.572	23.697	–0.010	0.000	0.65	67,027
		(5.55)	(–6.51)	(–1.93)	(6.73)	(4.54)	(–8.71)	(13.00)		
(2)	Big Firms	7.186	–5.269	–0.195	9.940	26.743	–0.018	0.000	0.65	33,433
		(4.61)	(–3.27)	(–2.89)	(5.28)	(3.16)	(–7.66)	(10.21)		
(3)	Small Firms	1.706	–4.110	0.094	3.389	6.964	–0.004	0.000	0.70	32,989
		(1.49)	(–3.62)	(2.12)	(2.30)	(1.12)	(–3.02)	(3.04)		

Table 13: Dynamism and Q-Models

The table examines the link between Q-model explanatory power (adjusted R^2) and its relationship with instrumented firm dynamism over time. Panel A reports the results of regressions in which the adjusted R^2 of the baseline Q-models in Figure 6. Panel B reports the results of Monte Carlo models in which the following simulation is run separately in each year. We consider 1000 random samples of 250 observations each drawn separately in each year. We then run the conditional Q-model in the given sample and we save the adjusted R^2 and the average instrumented dynamism (Panel B) or raw dynamism (Panel C). The result is a database with 20,000 observations (20 years x 1000 simulations) containing R^2 and average dynamism results. In Panel B, we regress the conditional Q-model's adjusted R^2 on the average instrumented dynamism for the given sample. Panel C is similar except that we use raw dynamism instead of instrumented dynamism. Instrumented dynamism is the fitted value from annual regressions of log dynamism on the following set of plausibly exogenous variables and their interactions with above median firm size: international competition complaints from distant peers, international growth mentions from distant peers, product market fluidity of peers, the instrumented volatility measure from **?**, and also controls for log assets and log firm age. Results in both panels also include year fixed effects.

Row	Dependent Variable	Subsample	Time Trend	Adj R^2	# Obs
		Panel A: Subsample Q Model R^2 Time Trends			
(1)	ARSQ of CAPX/assets	All Firms	0.006	0.525	20
			(4.46)		
(2)	ARSQ of CAPX/assets	High Pred. Dynamism	0.005	0.327	20
			(2.96)		
(3)	ARSQ of CAPX/assets	Low Pred. Dynamism	0.001	0.050	20
			(0.98)		
(4)	ARSQ of R&D/assets	All Firms	0.007	0.817	20
			(8.97)		
(5)	ARSQ of R&D/assets	High Pred. Dynamism	0.009	0.824	20
			(9.19)		
(6)	ARSQ of R&D/assets	Low Pred. Dynamism	0.002	0.143	20
			(1.73)		

Row	Dependent Variable	Instrumented Dynamism	Inst. Dyn. x Time Trend	Adj R^2	# Obs
		Panel B: Monte Carlo Q Model R^2 vs Instrumented Dynamism			
(7)	CAPX/assets	0.840		0.38	20,000
		(5.19)			
(8)	CAPX/assets	–0.002	0.103	0.38	20,000
		(–0.01)	(3.68)		
(9)	R&D/assets	2.739		0.26	20,000
		(13.00)			
(10)	R&D/assets	1.501	0.152	0.26	20,000
		(4.11)	(4.16)		
		Panel C: Monte Carlo Q Model R^2 vs Raw Dynamism			
(11)	CAPX/assets	0.942		0.38	20,000
		(17.16)			
(12)	CAPX/assets	0.332	0.070	0.39	20,000
		(3.34)	(7.37)		
(13)	R&D/assets	0.947		0.26	20,000
		(13.17)			
(14)	R&D/assets	0.565	0.044	0.26	20,000
		(4.34)	(3.52)		

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

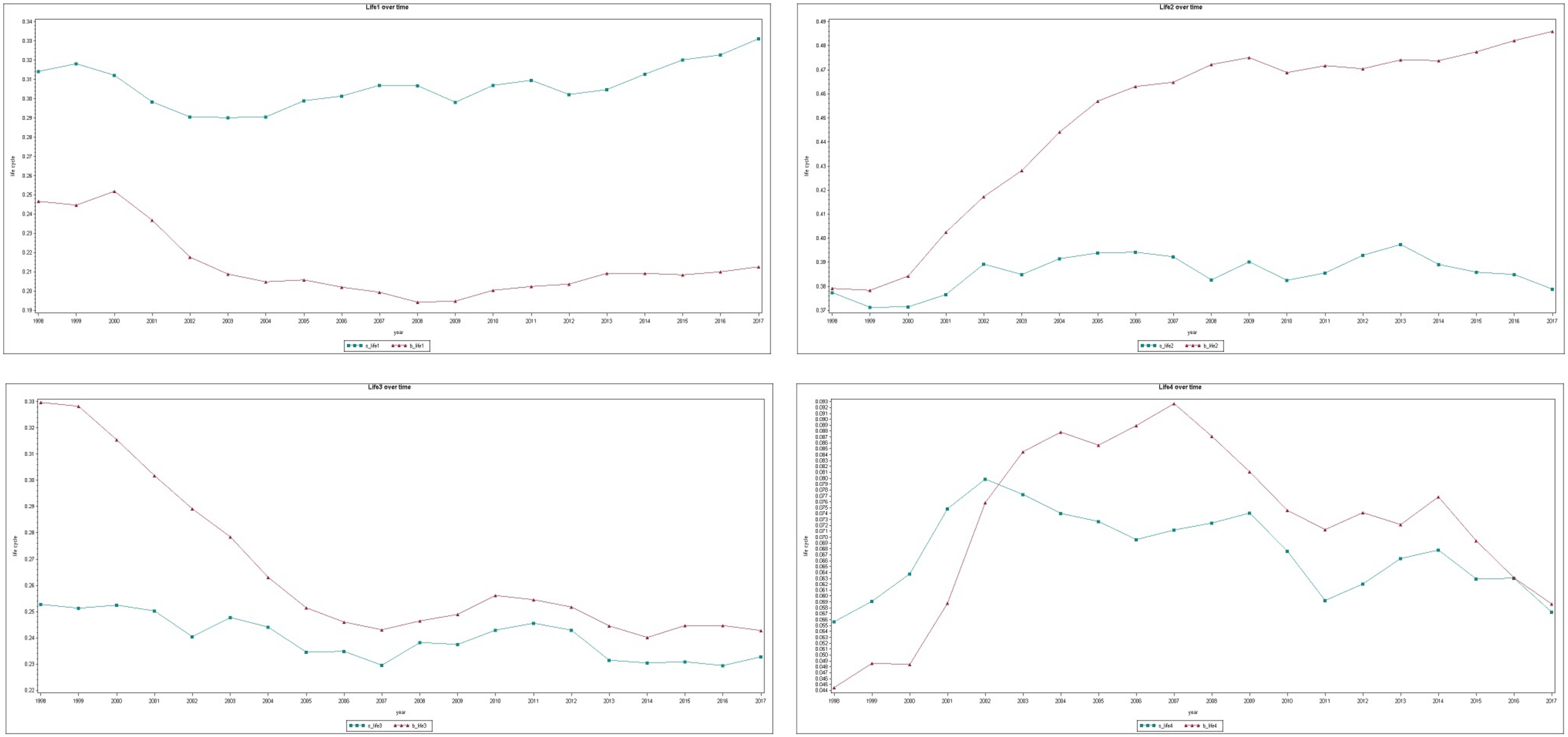


Figure 2: Average Firm Dynamism index, which is defined as $(1 - Life3)$, for firms in the bottom and top quartiles of firms by asset size, computed annually.

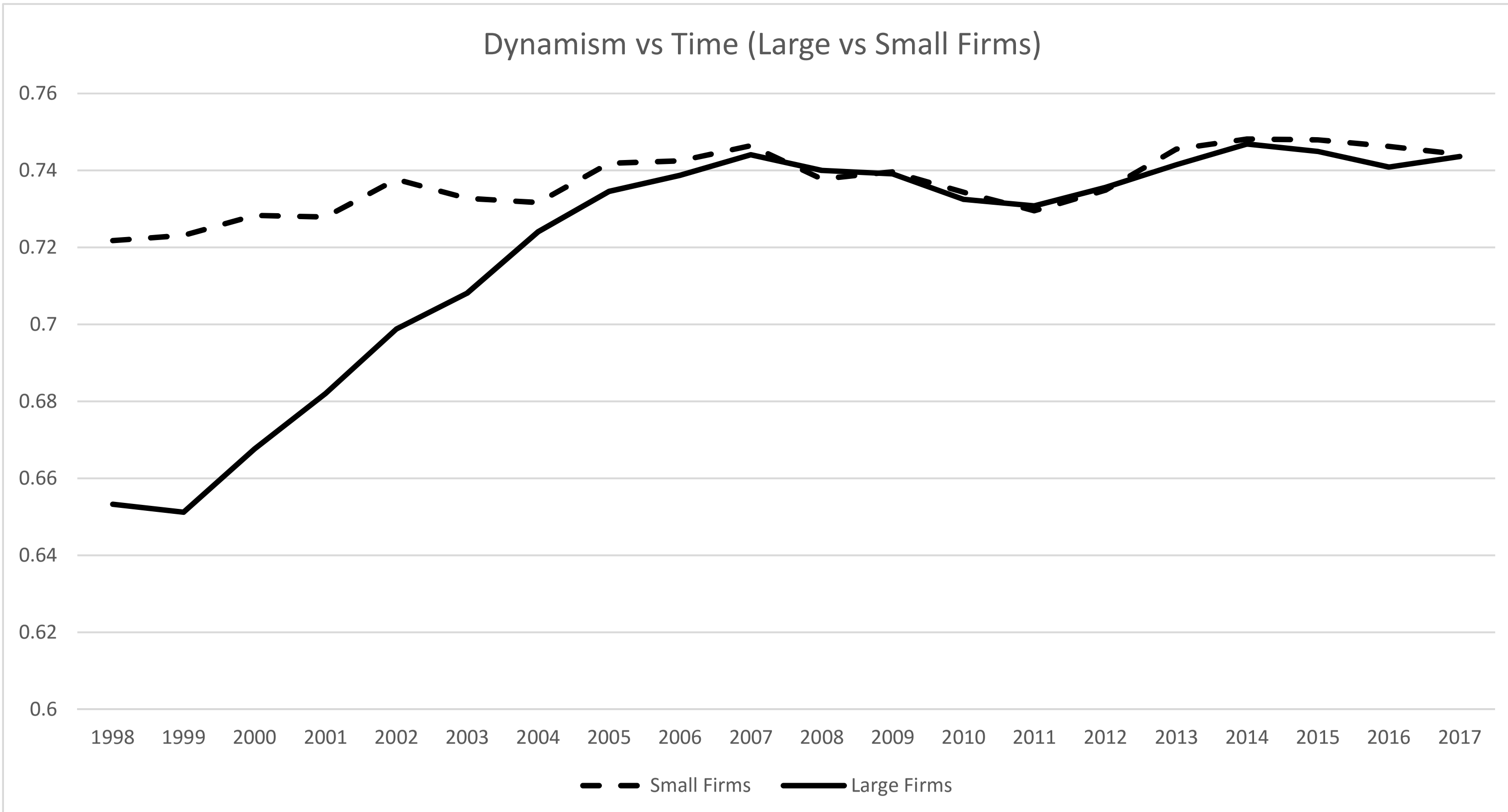
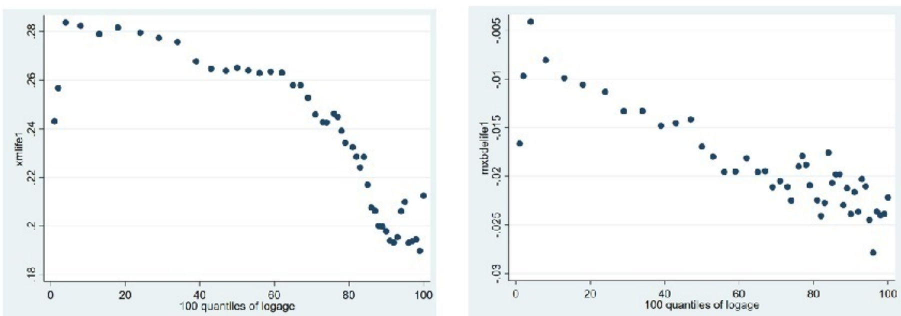
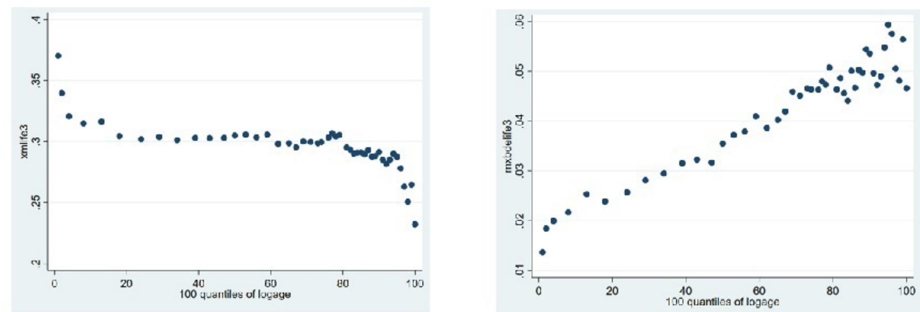


Figure 3: We report two graphs for each life cycle stage variable. The left graph for each plots the mean raw values against percentiles based on age for all sample firms. The right graph shows the mean values after each life variable is regressed on both firm and year fixed effects and then plotted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

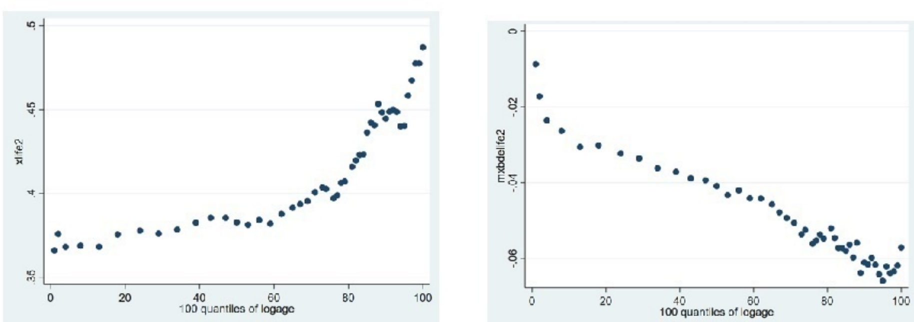
Life 1:



Life 3:



Life 2:



Life 4:

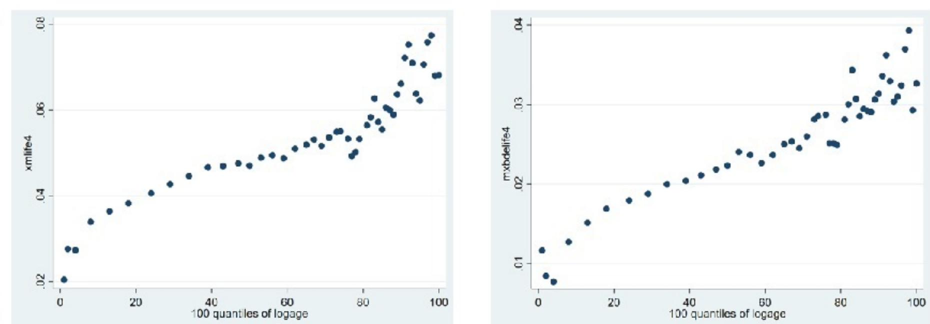
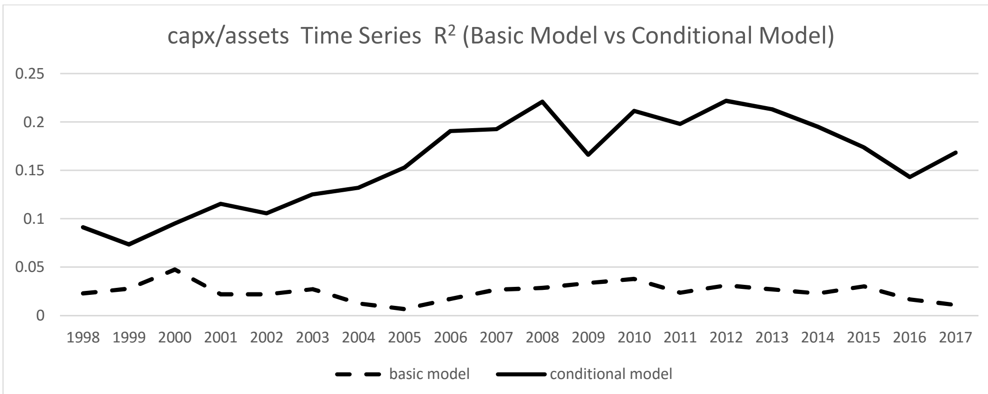


Figure 4: Plot of the R^2 of the annual cross sectional regressions in Tables 8 and 9. The Basic Classic model does not adjust for differences in the investment-Q relationship for different values of the life variables. The Conditional model adjusts for the level of the Life variables and their interaction with Tobin's Q.



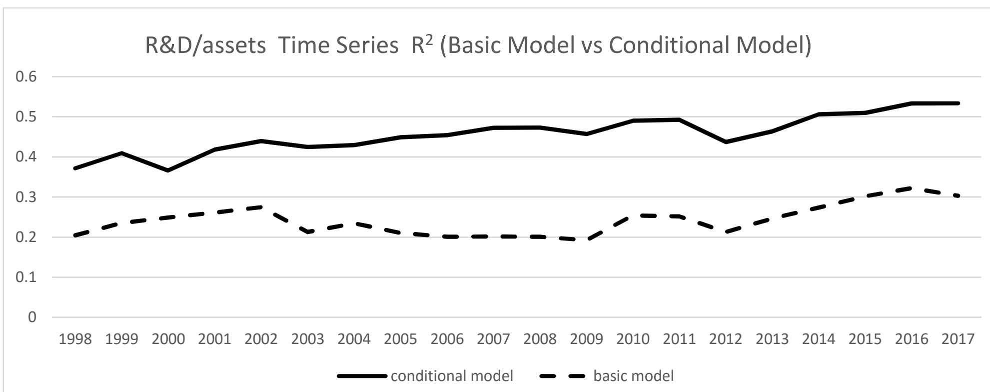
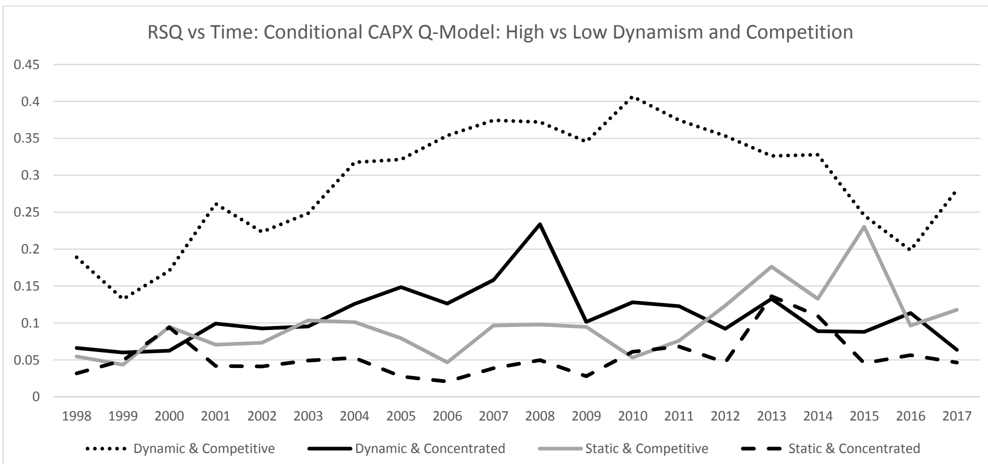


Figure 5: Plot of the R^2 of the annual cross sectional regressions using the conditional model as shown in Tables 8 and 9. The Conditional model adjusts for the level of the Life variables and their interaction with Tobin's Q. The upper figure displays results for the CAPX-Q model and the lower figure displays results for the R&D-Q model. Dynamism is defined as $(1-life3)$ and competition is defined as the TNIC HHI from Hoberg and Phillips (2016). In each year, we perform independent sorts of the full sample into above and below median values of dynamism and TNIC HHI. Note that the four subsamples are quite evenly balanced in terms of number of observations, which arises because dynamism and HHIs are less than 5% correlated.



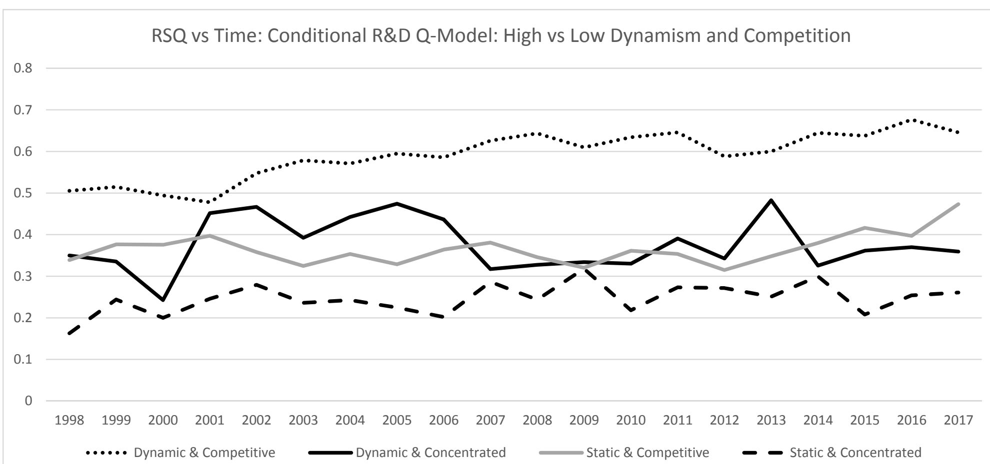
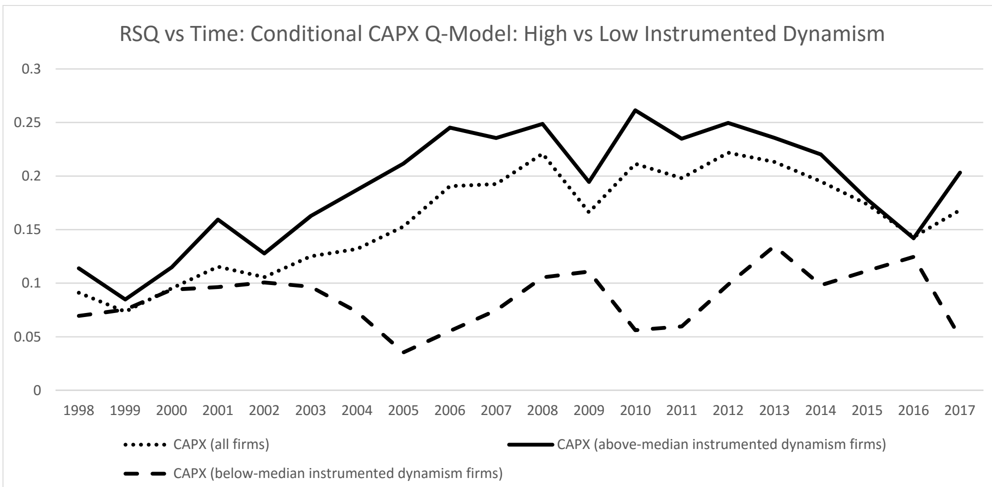
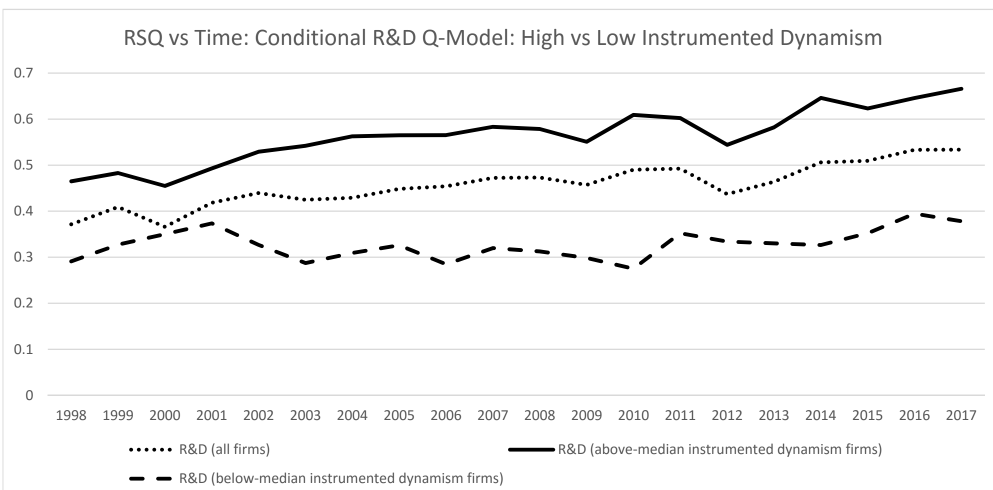


Figure 6: Plot of the R^2 of the annual cross sectional regressions using the conditional model as shown in Tables 8 and 9. The Conditional model adjusts for the level of the Life variables and their interaction with Tobin's Q. The upper figure displays results for the CAPX-Q model and the lower figure displays results for the R&D-Q model. Dynamism is defined as $(1 - life3)$. Instrumented dynamism is based on the first stage model depicted and explained in Table 12.





Online Appendix

Product Life Cycles in Corporate Finance

Not Intended for Publication

Table IA.1: Validation: Product Market Fluidity and Product Description Growth

The table reports OLS estimates for our sample of annual firm observations from 1998 to 2017. An observation is one firm in one year. The dependent variable is product market fluidity (see Hoberg, Phillips and Prabhala (2014)) or product description growth (see Hoberg and Phillips (2010)) in Panel A and Panel B, respectively. All specifications include firm and year fixed effects. Standard errors are clustered by firm. t-statistics are in parentheses.

Row	Life1	Life2	Life4	Log Age	Log Assets	Business Descr. Size	Whole 10-K Size	R&D Assets	Tobin's Q	Obs/ Adj R^2
				Panel A: Dependent Variable = Product Description Growth						
(1)	0.116	0.023	–0.088			–0.333	0.000			63,776
	(5.08)	(1.35)	(–4.22)			(–59.66)	(4.89)			0.19
(2)	0.095	0.009	–0.078	–0.062	0.018	–0.343	0.000	0.004	0.006	63,713
	(4.18)	(0.53)	(–3.71)	(–7.51)	(6.33)	(–59.58)	(3.87)	(0.21)	(8.21)	0.20
				Panel B: Dependent Variable = Product Market Fluidity						
(3)	1.194	0.433	0.317			2.072	0.000			64,419
	(6.66)	(3.17)	(1.99)			(42.38)	(4.45)			0.82
(4)	1.008	0.313	0.425	–0.624	0.194	1.977	0.000	0.612	0.037	64,356
	(5.70)	(2.29)	(2.66)	(–8.47)	(7.79)	(40.58)	(3.18)	(3.27)	(6.15)	0.83

Table IA.2: Investment Panel Data Regressions (Robustness using Peters and Taylor (2017) Q)

The table reports results from firm-year panel data investment-Q regressions from 1998 to 2017. The dependent variable is ex post R&D/assets (Panels A), CAPX/Assets (Panel B), SDC Acquisitions (Panel C), and SDC Targets (Panel D). In each panel, we consider three models. The "OLS" model uses life cycle variables based on the focal firm itself and includes firm and year fixed effects. The first "IV" model also includes firm and year fixed effects and uses (as instruments) the life cycle variables of the TNIC industry peers of the peers of the focal firm (peers two steps away have no direct links to the focal firm and their life cycle stages are thus more plausibly exogenous from the perspective of the focal firm. The second "IV" model uses NAICS-4 x year fixed effects. All dependent variables are based on the focal firm's investment policies. 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 Tobin's Q, and size plus age controls. 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 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	Tobin's 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)	OLS (Firm, Year FE)	0.007	0.000	-0.052	0.067	0.012	0.030	0.018	-0.001	-0.001	0.008	0.000	-0.053	0.73	66,319
		(16.39)	(0.25)	(-14.5)	(8.50)	(2.71)	(5.21)	(6.62)	(-0.70)	(-0.31)	(2.19)	(0.44)	(-15.3)		
(2)	IV (Firm, Year FE)	0.007	0.000	-0.052	1.303	0.435	0.107	0.040	0.004	-0.031	-0.023	-0.003	-0.020	0.00	64,449
		(16.39)	(0.25)	(-14.5)	(2.83)	(2.73)	(0.34)	(6.36)	(1.03)	(-3.50)	(-0.77)	(-0.61)	(-1.19)		
(3)	IV	0.007	0.000	-0.052	0.322	-0.092	0.430	0.037	0.003	-0.027	0.032	0.000	-0.025	0.00	65,607
	(NAICS x Year FE)	(16.39)	(0.25)	(-14.5)	(5.89)	(-1.88)	(2.73)	(7.01)	(0.75)	(-3.44)	(1.96)	(0.39)	(-6.60)		
								Panel B: CAPX/Assets							
(4)	OLS (Firm, Year FE)	0.008	-0.010	-0.060	0.017	-0.008	-0.035	-0.006	0.027	0.009	0.009	-0.011	-0.056	0.50	66,319
		(12.81)	(-6.72)	(-14.4)	(1.61)	(-0.87)	(-3.08)	(-1.58)	(5.31)	(1.71)	(0.95)	(-7.47)	(-13.4)		
(5)	IV (Firm, Year FE)	0.008	-0.010	-0.060	-0.571	-0.050	0.443	-0.018	0.059	-0.006	0.044	-0.004	-0.064	0.00	64,449
		(12.81)	(-6.72)	(-14.4)	(-0.78)	(-0.20)	(0.90)	(-1.63)	(4.68)	(-0.36)	(0.86)	(-0.54)	(-2.28)		
(6)	IV	0.008	-0.010	-0.060	0.099	0.334	-0.648	-0.004	0.047	-0.006	-0.065	0.002	-0.001	0.00	65,607
	(NAICS x Year FE)	(12.81)	(-6.72)	(-14.4)	(1.46)	(4.80)	(-2.46)	(-0.45)	(4.58)	(-0.43)	(-2.39)	(3.50)	(-0.17)		
								Panel C: SDC Acquisition Dummy							
(7)	OLS (Firm, Year FE)	0.006	0.010	-0.027	0.058	-0.017	-0.215	-0.004	0.013	0.010	0.019	0.006	-0.022	0.26	66,319
		(10.29)	(2.10)	(-1.80)	(1.46)	(-0.55)	(-5.61)	(-1.21)	(4.36)	(2.79)	(1.79)	(1.34)	(-1.47)		
(8)	IV (Firm, Year FE)	0.006	0.010	-0.027	1.541	-0.077	-1.471	-0.002	0.019	0.005	-0.090	-0.015	0.002	0.00	64,449
		(10.29)	(2.10)	(-1.80)	(1.16)	(-0.16)	(-1.86)	(-0.21)	(2.58)	(0.36)	(-1.19)	(-1.22)	(0.04)		
(9)	IV	0.006	0.010	-0.027	-0.734	-0.840	0.620	-0.001	0.003	0.010	0.090	0.076	-0.032	0.00	65,607
	(NAICS x Year FE)	(10.29)	(2.10)	(-1.80)	(-3.19)	(-3.72)	(0.73)	(-0.10)	(0.36)	(0.53)	(1.17)	(33.16)	(-1.69)		
								Panel D: SDC Target Dummy							
(10)	OLS (Firm, Year FE)	-0.001	0.041	0.044	-0.029	-0.004	0.076	-0.002	-0.003	0.003	-0.024	0.043	0.042	0.20	66,319
		(-3.28)	(11.28)	(3.65)	(-0.83)	(-0.16)	(2.24)	(-0.80)	(-1.61)	(0.87)	(-3.08)	(11.68)	(3.42)		
(11)	IV (Firm, Year FE)	-0.001	0.041	0.044	-1.784	-0.684	1.586	-0.017	-0.011	0.021	0.122	0.065	-0.039	0.00	64,449
		(-3.28)	(11.28)	(3.65)	(-1.33)	(-1.45)	(1.81)	(-1.50)	(-1.63)	(1.38)	(1.32)	(4.95)	(-0.80)		
(12)	IV	-0.001	0.041	0.044	0.031	-0.212	2.248	-0.013	-0.016	0.013	0.123	0.055	0.006	0.00	65,607
	(NAICS x Year FE)	(-3.28)	(11.28)	(3.65)	(0.16)	(-1.17)	(2.99)	(-1.17)	(-2.43)	(0.95)	(1.74)	(26.94)	(0.37)		

Table IA.3: Investment Panel Data Regressions (Measurement-Error Corrected using Erickson and Whited (2000))

This table is run in the same way that Table 6 in the main paper (titled "Investment Panel Data Regressions") is run with two modifications: (1) we run measurement-error-corrected regression model from Erickson and Whited (2000) and (2) we consider both the basic measure of Tobin's Q as well as the measure suggested by Peters and Taylor (2017) as noted in the first column (we thank the authors for providing their data via WRDS). The measurement error model is implemented using the Stata command "xtewreg" and we thank Toni Whited for providing the code for this routine on her website. In all models, we assume the default of 5 cumulants. In the conditional model, we assume 4 mismeasured variables: Tobin's Q and the 3-D life vector. We do not assume 4 mismeasured dimensions due to the fact that the life vector sums to one and so it only has 3 degrees of freedom. In the basic model, we assume only one mismeasured variable: Tobin's Q.

The table reports results from firm-year panel data investment-Q regressions from 1998 to 2017. The dependent variable is ex post R&D/assets (Panels A), CAPX/Assets (Panel B), SDC Acquisitions (Panel C), and SDC Targets (Panel D). All dependent variables are based on the focal firm's investment policies. 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 Tobin's Q, and size plus age controls. 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 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	Tobin's 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)	Base Q	0.083	-0.008	0.018	0.162	-0.047	-0.052	0.106	-0.010	-0.062	0.008	-0.012	-0.006	0.38	68,899
		(37.40)	(-11.06)	(9.82)	(14.57)	(-6.80)	(-6.99)	(44.77)	(-4.19)	(-17.87)	(0.90)	(-24.26)	(-5.83)		
(2)	P &T Q	0.023	-0.008	-0.003	0.147	-0.047	-0.023	0.043	-0.008	-0.017	0.004	-0.004	-0.018	0.35	66,319
		(24.23)	(-20.80)	(-1.95)	(17.85)	(-10.61)	(-4.52)	(35.60)	(-5.48)	(-9.18)	(0.93)	(-14.10)	(-18.75)		
								Panel B: CAPX/Assets							
(3)	Base Q	0.008	0.004	-0.008	-0.014	0.018	-0.023	-0.001	0.008	0.007	0.012	0.004	-0.009	0.07	68,899
		(9.14)	(11.96)	(-7.18)	(-2.66)	(4.40)	(-5.45)	(-0.56)	(4.36)	(4.07)	(3.05)	(10.89)	(-8.87)		
(4)	P &T Q	0.009	0.006	-0.020	-0.024	0.025	-0.019	0.001	0.019	0.008	0.001	0.005	-0.020	0.17	66,319
		(18.94)	(15.35)	(-14.36)	(-3.16)	(4.38)	(-3.13)	(1.60)	(5.40)	(2.54)	(0.14)	(14.49)	(-16.70)		
								Panel C: SDC Acquisition Dummy							
(5)	Base Q	-0.006	0.069	-0.022	0.108	-0.002	0.081	-0.018	0.018	0.052	0.039	0.072	-0.010	0.12	68,899
		(-3.14)	(43.47)	(-5.00)	(3.96)	(-0.11)	(4.18)	(-7.49)	(3.66)	(9.07)	(2.64)	(47.55)	(-2.37)		
(6)	P &T Q	0.001	0.072	-0.020	0.115	0.001	0.000	0.013	0.005	0.001	-0.003	0.073	-0.010	0.10	66,319
		(3.31)	(46.24)	(-4.48)	(4.26)	(0.06)	(-0.02)	(8.57)	(2.21)	(0.25)	(-0.31)	(45.99)	(-2.32)		
								Panel D: SDC Target Dummy							
(7)	Base Q	0.009	0.051	0.045	0.053	0.099	0.104	0.002	-0.001	-0.001	-0.107	0.050	0.038	0.10	68,899
		(5.87)	(37.70)	(14.40)	(2.91)	(7.81)	(6.87)	(1.44)	(-0.28)	(-0.16)	(-5.45)	(35.58)	(11.84)		
(8)	P &T Q	0.001	0.052	0.045	0.165	0.083	0.095	-0.015	-0.002	0.015	-0.056	0.055	0.042	0.10	66,319
		(2.04)	(36.31)	(13.14)	(8.17)	(5.94)	(6.24)	(-17.90)	(-0.96)	(7.16)	(-5.21)	(38.19)	(12.35)		

Table IA.4: Investment Panel Data Regressions (with Lagged Dependent Variable)

The table reports results from firm-year panel data investment-Q regressions from 1998 to 2017. The dependent variable is ex post R&D/assets (Panels A), CAPX/Assets (Panel B), SDC Acquisitions (Panel C), and SDC Targets (Panel D). In each panel, we consider two models. The "Baseline" model uses OLS includes firm and year fixed effects. The "Arrellano-Bond" model is similar and further ensures econometric biases associated with the joint use of firm fixed effects and lagged dependent variables do not induce bias. All dependent variables are based on the focal firm's investment policies. 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 Tobin's Q, and size plus age controls. 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 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.

Row	Model	Life1	Life2	Life4	TobQ x Life1	TobQ x Life2	TobQ x Life3	TobQ x Life4	Log Assets	Log Age	Lagged Dep Var	Lagged Dep Var x TobQ	Adj R^2	# Obs
								Panel A: R&D/Assets						
(1)	Baseline	0.025	–0.002	0.000	0.009	–0.002	0.001	0.004	–0.012	–0.003	0.524	0.023	0.89	68,899
		(5.80)	(–0.69)	(–0.01)	(4.89)	(–2.10)	(0.29)	(0.91)	(–16.03)	(–2.31)	(34.43)	(8.70)		
(2)	Arrellano-Bond	0.025	–0.002	0.000	0.009	–0.002	0.001	0.004	–0.012	–0.003	0.524	0.023	0.00	60,011
		(6.43)	(–0.76)	(–0.01)	(5.33)	(–2.27)	(0.32)	(0.96)	(–17.84)	(–2.54)	(38.93)	(9.81)		
								Panel B: CAPX/Assets						
(3)	Baseline	0.013	–0.002	–0.023	–0.006	0.016	0.003	0.006	–0.012	–0.014	0.338	0.054	0.61	68,899
		(2.79)	(–0.51)	(–5.11)	(–3.98)	(10.69)	(1.75)	(1.85)	(–16.73)	(–7.00)	(22.18)	(7.88)		
(4)	Arrellano-Bond	0.013	–0.002	–0.023	–0.006	0.016	0.003	0.006	–0.012	–0.014	0.338	0.054	0.00	60,011
		(3.03)	(–0.56)	(–5.55)	(–4.31)	(11.63)	(1.90)	(1.98)	(–18.11)	(–7.59)	(24.58)	(8.57)		
								Panel C: SDC Acquisition Dummy						
(5)	Baseline	0.049	–0.022	–0.197	–0.031	0.038	0.039	0.050	0.004	–0.010	0.035	0.008	0.27	68,899
		(1.29)	(–0.75)	(–5.43)	(–5.66)	(6.33)	(5.22)	(3.22)	(0.97)	(–0.73)	(6.77)	(3.33)		
(6)	Arrellano-Bond	0.049	–0.022	–0.197	–0.031	0.038	0.039	0.050	0.004	–0.010	0.035	0.008	0.00	60,011
		(1.42)	(–0.82)	(–5.93)	(–6.12)	(6.81)	(5.65)	(3.60)	(1.07)	(–0.80)	(7.37)	(3.62)		
								Panel D: SDC Target Dummy						
(7)	Baseline	–0.026	–0.008	0.064	0.005	–0.011	–0.005	–0.062	0.039	0.064	–0.003	0.002	0.20	68,899
		(–0.76)	(–0.31)	(1.94)	(1.08)	(–2.40)	(–0.83)	(–4.55)	(11.26)	(5.70)	(–0.58)	(0.64)		
(8)	Arrellano-Bond	–0.026	–0.008	0.064	0.005	–0.011	–0.005	–0.062	0.039	0.064	–0.003	0.002	0.00	60,011
		(–0.83)	(–0.34)	(2.12)	(1.18)	(–2.62)	(–0.90)	(–5.36)	(12.38)	(6.23)	(–0.63)	(0.69)		