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Life Cycles of Firm Disclosures

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ABSTRACT

We propose that the product life cycle is important in understanding firm disclosure policies and test this hypothesis using a 4-dimensional text-based life cycle model. Mature-stage firms disclose more, consistent with lowering search costs for an outward-focused investment strategy seeking synergistic partners. Early-stage life cycle firms are secretive, consistent with inward-focused organic investment and mitigating competitive threats. These results obtain across disclosure measures relating to intellectual property, redaction of contracts, readability, and conference calls. A quasi-natural experiment based on waves of rapid depreciation of protected intellectual property, and internet co-search tests targeting specialized disclosure sender and receiver hypotheses, reinforce this interpretation.

1 Introduction

Research on the disclosure policies of firms has long recognized the incentives that firms have to be secretive and to reduce disclosure when facing aggressive competition (Verrecchia 2001). Although this incentive can be offset by incentives to disclose more to investors to mitigate financial and regulatory constraints[1], few studies focus on interactions between firms that favor increasing a firm's disclosure. In this paper, we show that the firm's and its rivals' disclosures are shaped by their exposure to their product life cycle. This channel is distinct from the competitive interactions studied in the literature and can generate additional incentives to be secretive or to disclose.

A key problem of traditional data and methods in the analysis of life cycles is measurement. We solve this problem by using unstructured textual data from SEC filings to obtain 4-dimensional representations of the firm's exposure to the life cycle stages of its product portfolio. More specifically, we use advanced computational linguistic methods rooted in "Chained Context Discovery" (see Cimiano, 2010) to measure the firm's life cycle status at an annual frequency.[2] This anchor-phrase technology uses multiple vocabularies and word-pair proximity to identify unambiguous firm statements indicating stages of the life cycle. We additionally follow Bernard, Blackburne, and Thornock (2019) and use crowd-sourced web queries to develop an additional "proof of mechanism" regarding predicted web activity.

We propose that the incentive of firms in the mature stage of the product life cycle to disclose more than control firms is rooted in firms' optimal investment strategies. Hoberg and Maksimovic (2019) show that firms in earlier stages of the product life cycle are focused on (inward-facing) organic investment in the form of R&D and CAPX. These investments are aimed at establishing a defensible position in the product market, and because these market positions are not yet established, managers are

[1] Such as Diamond and Verrecchia (1991), Healy and Palepu (2001), Lambert, Leuz, and Verrecchia (2007), Ellis, Fee, and Thomas (2012), Bourveau, She, and Zaldokas (2020).

[2] See Hoberg and Maksimovic (2019) for the derivation of the metrics. We thank Christopher Ball and metaHeuristica for providing technology and software to facilitate our use of this technology in a high speed and easy-to-use database.

particularly concerned about product substitution threats from competitors. These prior results are foundational for our current study and we will refer to them frequently. Mature stage firms, in contrast, have stable and established positions in the product market, and are focused on (outward-facing) inorganic investment in the form of mergers and acquisitions. These investments are rooted in complementary relationships with product market peers. Thus, the life cycle moderates whether firms view peers primarily as substitutes or complements.[3] In turn, these relations between firms and their peers predicts whether informative disclosure is likely to be value destroying or value creating and, as we show, drives disclosure policy. We thus propose new real incentives to either *increase or decrease* disclosure. Our predictions are novel to the literature, and contrast with the prevalent view that product market peers are always a competitive threat that incentivize reduced disclosures.

Our main empirical findings are that firms with more exposure to the mature product life cycle stage disclose substantially more along many dimensions. They disclose more innovations in the form of patents relative to trade secrets. They disclose more operational details as they are less likely to redact information in their 10-K. Their disclosures are more readable to further provide clear interpretations of their financial statements. They also provide more information content in their earnings calls. In contrast, firms in the early stage of the product life cycle strongly favor secrecy and provide less disclosure on these same dimensions.

Consistent with our hypothesized focus on the interaction of the focal firm with its peers, we find that not only does a firm's own-exposure to the life cycle matter for disclosures, but the life cycle exposures of the firm's product market peers also matters in determining firm disclosure strategies. Our estimates of the effects of the product life cycle on disclosures are strongest when the life stages of the disclosing firm match the life cycle stages of the peer firms that receive the disclosure signal. When a firm's peers are in the mature life cycle stage, and are also potentially seeking synergistic opportunities, we find that the focal firm's disclosure strategy es-

[3] See Wall Street Journal article (Dvorak and Wingfield 2011) for a depiction of how related peer firms can be seen as friend or foe in market surrounding the Google-Motorola merger.

pecially favors more informative disclosure. This is consistent with increased returns to disclosure as there are more strategic partners to attract and more inorganic investment opportunities to realize. On the margin, increased disclosure can improve inorganic investment efficiency in the form of M&A through at least two channels: (1) search cost reduction and more efficient matching of partners, and (2) through increased investment efficiency via improved information (see Goldstein, Yang, and Zuo (2020) for evidence of this channel in the context of the launch of the SEC EDGAR website).[4] In contrast, when a firm's peers have products in the early product development stage, the focal firm favors a secretive disclosure strategy. This is consistent with competitive substitution threats being particularly important when rivals are also pro-actively determining their own product placements (disclosure preserves any first mover advantages).

Because our hypothesis has direct predictions regarding both the sender and receiver of a firm's disclosures, we use the novel framework of Bernard, Blackburne, and Thornock (2019) to directly test the intensity at which product market peers download each others' disclosures. The authors use IP addresses to document the extent to which firms search one another's SEC filings using the EDGAR database, and document a link between co-search and mergers and acquisitions.[5] This approach offers significant econometric power, as the co-search data is available at the level of firm-pairs. We consider regressions where the extent of co-search is the dependent variable, and the life cycle stages of the pair of firms comprise our key explanatory variables. Consistent with our hypotheses, and providing rather direct evidence of our proposed mechanisms, we find that both early and mature product firms are more likely to search the filings of firms in like-product market stages. In contrast, we find that firms in other life cycle stages are less likely to search one another's filings. These results support our conjecture that the life cycle stages of both a firm's and its peers' products are jointly important in understanding disclosure policies.

[4]The theory in Goldstein and Yang (2015) shows further that additional benefits in the form of improved information for related investment strategies can also arise through this channel. Also see Goldstein and Yang (2017) for a broad review of these and related channels.

[5]We thank the authors for sharing their search data.

Our results are uniformly stronger for younger firms, which are more agile in selecting both pro-secrecy and pro-transparency disclosure policies through the product life cycle. Young firms with more products in the development stage are particularly secretive across all of our disclosure metrics. Additionally, young firms with mature products are particularly transparent relative to control firms. These tests have ample power because firm age is positively but only modestly (generally less than 20%) correlated with our product life cycle variables. These findings support Loderer, Stulz and Waelchli (2016), who argue that firms become more rigid as they age. In our context, this rigidity extends to firm disclosure policies, which we show are less reactive to product life cycle incentives as firms age.

Our findings contrast with the usual presumption that increased disclosures are strongly driven by the need to raise capital. We provide evidence that our life cycle findings are not limited to constrained firms disclosing for financing needs. Moreover, our results are consistent with Hoberg and Maksimovic (2019), who show that firms exposed to the late stage of the product life cycle do not issue much equity whereas firms exposed to the early stage do. Our findings thus indicate that, although mature-product firms are less active in external finance, they nevertheless increase disclosures likely to attract complementary firm inorganic growth opportunities. In contrast, firms with early stage life-cycle products decrease disclosures even though they on average demand more external financing. This is consistent with the view that although financial constraints matter, they tend to be modest for most of the relatively large publicly traded firms in our sample.

Although life cycles can be theoretically modeled as primitives, the issues surrounding life cycle stages are potentially endogenous, and we are unable to fully establish causality. However, we consider a quasi-natural experiment based on sectoral waves of rapidly depreciating protected intellectual property. Intuitively, a rapid loss of IP protection creates entry incentives for new firms and related incentives for existing firms to expand into the treated markets. Our thesis is that firms that are developing new products will primarily view the entry threat as unwanted competition, and will further curtail all forms of disclosure. In contrast, we expect firms with mature products will view the potential entrants as complementary, and will internalize additional opportunities for attracting inorganic alliances. We thus expect that firms with mature products will increase all forms of disclosure to attract the new partners. Our results strongly support these predictions, especially when the shock is measured at broader sectoral levels of granularity.[6]

In addition to the quasi-natural experiment and the co-search mechanism tests described above, we take additional steps to reduce the potential impact of endogeneity. We also include rigid firm fixed effects, which ensures that unobservable firm characteristics cannot explain our results. Our results are unified across many disclosure policies, and are also robust to including an array of controls such as firm age (the standard life cycles measure in the existing literature), size, and Tobin's Q.[7] Our results are also robust to excluding financials from our sample and to including controls for document size. Overall, our findings suggest a richer narrative and microfoundation for how firm relationships with product market peers might influence disclosure decisions. These findings can also inform regulatory debates, such as how can the SEC best offer scaled disclosure to emerging growth firms, and when should redaction be granted to firms seeking more secretive disclosures.

2 Overview and Related Literature

Initial work on disclosure focused on the communication between the firm and its investors, and argued that it is optimal for any except the lowest value firm to reveal its private information so that it is not pooled with less valuable firms by investors (see for example Grossman and Hart, 1980; Grossman, 1981; and Milgrom, 1981). Verrecchia (1983) noted that costs of disclosure may overturn this intuition if, for

[6]Denes, Duchin, and Harford (2018) also explore the link between patent expiration cycles and restructuring. However, their study is otherwise distinct as they address neither product life-cycles nor firm disclosures.

[7]We also note that our results are robust to dropping firms with below median market capitalization from our sample. Hence, our results cannot be explained by changes in disclosure requirements for "smaller reporting companies" during our sample.

example, the disclosure provides valuable information to rivals (see also Verrecchia, 2001). Ellis et al. (2012) analyze the trade-off between reducing information asymmetry to attract capital from market participants against the costs of aiding competitors by revealing proprietary information. Expanding this logic to technology markets, Cao et al. (2018) find that technological competition is negatively related to product-development press releases.

Our paper is related to Kim, Taylor, and Verrrechia (2020) who argue that, although the literature has focused separately on the aforementioned costs and benefits of voluntary disclosure, in reality they are jointly determined. The authors show that this leads to a non-linear relation between the costs and benefits, and thus the amount of disclosure, as the joint determinant varies. We propose and find that the trade-off between costs and benefits changes with the life cycle, and disclosure policies indeed are non-linear in the progression of the life cycle. Our work builds on earlier work by Bhattacharya and Ritter (1983), Maksimovic and Pichler (2001), and Awaya and Krishna (2020), who illustrate the the negative effects of early technological disclosures through competitors. Our work also builds on more recent work by Boot and Vladimirov (2020), who show how mature firms benefit from disclosures that promote what they term "co-option," competition on some dimensions and cooperation on other dimensions. Goldstein and Yang (2015) further show that such disclosure strategies can generate amplification-effects as traders can use the disclosed information to inform a wider array of investment projects, and in our context, such projects likely include synergistic alliances with other firms.

Our study is also related to recent work in both finance and accounting on life cycles using measures such as firm age. Loderer, Stulz and Waelchli (2016) argue that, as firms age, they become more rigid and less able to respond to growth opportunities. Arikan and Stulz (2016) show that acquisition activity follows a U-shaped pattern with respect to age. DeAngelo, DeAngelo and Stulz (2010) study the impact of firm life cycles on the probability of conducting seasoned equity offerings. Because our results are robust to including controls for age and age squared, we conclude that our text-based measures are unique. One interpretation is that we focus on product life cycles, whereas age measures institutional or organizational life cycle effects.

In an early study, Anthony and Ramesh (1992) examine life cycle effects on the cross-section of stock market reactions to unexpected events. They measure the life cycle using accounting-based proxies for firm growth (e.g. dividend payout, sales growth, and age). Dickinson (2011) extends this work to develop an accounting life cycle model based on cash flow patterns to explain firm profitability. The study also points out that capturing life cycles at the firm level is a difficult undertaking as firms are aggregations of multiple products. We address this challenge using textual analysis to model a disaggregated 4-D vector for each firm in each year.[8]

We argue that firms at different stages of their life cycles adopt different disclosure policies. Our analysis starts with the Abernathy and Utterback (1978) framework, which posits that over their life cycles, firms pass through four stages.[9] During the first stage, which we term Life1, firms focus on developing products. During Life2, the focus is on process innovations. As the market stablizes, Life3 firms focus on creating value from customers, and during the final stage, Life4, the firm's assets are redeployed. Hoberg and Maksmovic (2019) document a natural ordering of optimal investment strategies that follows the life cycle stages and show that competition and life cycle effects are equally important regarding the efficacy of investment Q-models. Crucial to our study, the authors show that early-stage firms focus on organic growth opportunities (inward focused) and mature-stage firms focus on inorganic growth such as acquisitions (outward focused). Their results help to motivate our hypotheses on voluntary disclosure strategies.

Life1 is associated with product development, where the firm maintains a valuable option to refine a product's market positioning and its technical specifications.

[8]Our product life cycle measures are fundamentally different from Dickinson (2011)'s measures as Online Appendix Table A4 and Table A5 show that there is little correlation between our measures and those in Dickinson (2011). Unsurprisingly given their low correlation and their distinct foundation, Dickinson's (2011) life cycle variables do not generate our findings.

[9]More recently, in a series of influential works, Christensen (1993, 2013) takes a similar perspective and notes that industry evolution can often be described as competition between disruptors (typically young firms) and established firms using very different strategies.

Disclosures about these developments are valuable to competitors as they can take countermeasures. Because the focal firm does not yet have an established public market presence, competitors might not otherwise observe this information. Life1 thus entails an "inward-focused" organic investment strategy with few benefits and high costs of disclosure. Consistent with Glaeser (2018), we expect that these incentives favoring secrecy will impact a wide array of disclosure policies including trade secrecy, redaction, and readability. Consistent with Kankanhalli et. al. (2019), we further expect that such information restrictions will increase investor estimates of firm value. We formalize this in hypothesis H1:

H1: Exposure to Life1 will be associated with increased redactions, increased reliance on trade secrets relative to patents, and less readable 10-Ks.

In contrast, firms with high Life3 exposure operate in markets that are stable and create value from existing product portfolios. Since these firms (by definition) have products that are visible and already-known in the public market, there is less downside risk to disclosing more. Further, as Hoberg and Maksimovic (2019) show, Life3 firms grow by investing most in inorganic (outward focused) investment and acquisitions.[10]. Disclosure can reduce the cost of this strategy, as Rhodes-Kropf and Robinson (2008), Hoberg and Phillips (2010), and Bena and Li (2014) argue that the matching of bidders and targets is key to creating value from acquisitions.

H2: Exposure to Life3 will be associated with decreased redaction, decreased reliance on trade secrets relative to patents, and more readable financial statements.

Theories of disclosure often differ on the crucial dimension of which "receiver" is the focal firm (the "sender") optimizing the disclosure for? For example, if the main objective of financial disclosures is to facilitate external financing, then investors are the intended receiver, as they form opinions about valuation and the cost of capital from the disclosures. Our hypothesis is different in an important and testable way. We assume that the receiver is the set of peer firms in the focal firm's broad indus-

[10]This is related to the finding by Maksimovic and Phillips (2008) that conglomerate firms, which tend to be older and larger, grow more by acquisition than by organic investment.

try sector. This distinguishing feature of our thesis creates additional specialized predictions about the joint characteristics of the focal firm and its peers, and when incentives to customize disclosure will be strongest. This logic also leads to strong predictions regarding which specific pairs of firms will have the strongest incentives to actually download one anothers' disclosure filings. This leads to the following sender vs receiver hypothesis:

H3 [Sender vs Receiver]: Hypothesis H1's predictions will be sharpest when the focal firm and its product market peers are jointly highly exposed to Life1. H2's predictions will be sharpest when both are jointly exposed to the Life3 stage. Moreover, firm-pairs will download one anothers' filings most when the pair is either jointly highly exposed to Life1, or jointly highly exposed to Life3.

The predictions of H3 arise from basic tradeoffs. Intuitively, a Life1 firm seeking to preserve its proprietary advantages regarding product placement will feel particularly strong incentives to do so when its peers are also seeking to optimize product placement. Here, secrecy most strongly insures against a loss of any first-mover advantage Life1 firms with proprietary information maintain. Analogously, a Life3 firm seeking inorganic partners will have particularly strong incentives to disclose more when its sector peers are also in Life3 and seeking such partnerships. These focal firm and peer effects are reinforcing, as the marginal benefit of either the Life1 or Life3 strategy becomes amplified when peers are facing similar tradeoffs. A consequence of H3 is that we should find strong results when we interact a focal firm's life cycle stages with that of its peers.

H3 also has specialized implications regarding which firms will download which other firms' 10-Ks (which firm-pairs are explicitly senders and receivers). In particular, Life1 firms should focus their search on other Life1 firms, and Life3 firms should most search other Life3 firms. This last prediction can be broadened, as Life3 firms might search the broader set of potential targets including all that have a visible product portfolio. We test these predictions directly using the approach of Bernard, Blackburne, and Thornock (2019), who use IP addresses available in the SEC Edgar log files to tag downloading patterns across all pairs of firms in each year.[11]

Exposure to Life2 is associated with a focus on improving process efficiency. Since the firm's products are already in the market, some information that was confidential in the Life1 stage no longer needs protection. In addition, while much process investment will be internal, some is also likely to be directed to vendors specializing in machine tools and business software. The confluence of these factors suggests that a Life2 firm will be partially sensitive to the downside risks of disclosure, and also partially sensitive to the upside potential of inorganic investments. We thus expect Life2 firm disclosures to be somewhat "average" in the distribution.

Firms with exposure to Life4 likely have some focus on divesting some of their assets. Similar to Life3 firms, they are seeking parties with whom to transact. Because Life4 firms might need to redeploy their assets to other markets (given the poor outlook of their existing markets), increased disclosure might offer lower marginal gains. On the other hand, Hoberg and Maksimovic (2019) find that Life4 firms seek risk taking opportunties to escape decline. This strategy requires innovation and can benefit from increased secrecy. We thus expect Life4 firms to exhibit disclosures that are somewhat "average" in the distribution.

3 Data and Methods

3.1 Data

Our sample begins with the universe of Compustat firm-years with 10-K data available between 1997 and 2017. 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

[11] Other studies using the server log files include Lee, Ma, and Wang, 2015; Drake, Roulstone, and Thornock, 2015; Ljungqvist and Qian, 2016; and Drake, Johnson, Roulstone, and Thornock, 2020. These issues are also related to corporate learning (see Roychowdhury, Shroff, and Verdi, 2019; and Leary and Roberts, 2014).

CRSP/COMPUSTAT database using the central index key (CIK), and the mapping table provided in the WRDS SEC Analytics package.

We also obtain additional data from Compustat to construct control variables such as firm age and Tobin's Q[12]. We use Herfindahl-Hirschman index based on Text-based Network Industry Classifications (TNIC HHI) from Hoberg and Phillips (2010, 2016) as our main competition measure. This measure is firm-specific, and is based on the TNIC industry classification.

3.2 The Product Life Cycle

Our approach to measuring life cycles echoes that used in Hoberg and Maksimovic (2019) and our goal is to use direct textual queries of 10-K text to identify the life cycle stage of a firm's product portfolio. This is done using metaHeuristica text processing software, which has pre-built modules for fast and highly flexible querying, while producing output that is easy to interpret.[13]

The "anchor-phrase" methodology we adopt has been used in past studies including Hoberg and Maksimovic (2015), Hoberg and Moon (2017) and Fresard, Hoberg, and Phillips (2020). 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

[12]Tobin's Q $= ((CSHO * PRCC_F) + DLC + DLTT + PSTKL)/AT$

[13]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.

product discontinuation.

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. We thus 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).[14]

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

[14] 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.

must contain at least one word from each of the first two lists (List A and List B below), and must not contain any words from the third list below (List C). The exclusion ensures that Life3 is characterized as the static state of product maturity as the exclusion list is based on the union of the other three dynamic life cycle stages.

Life3 List A: product OR products OR service OR services

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

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

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

Life4 List A: product OR products OR service OR services OR inventory OR inventories OR operation OR operations

Life4 List B: obsolete OR obsolescence OR discontinued OR discontinue OR discontinuance OR discontinuation OR discontinues OR discontinuing

The above queries result 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 in the management's discussion and analysis (MD&A) section of the 10-K. To avoid outliers, we limit each life cycle exposure to unity. We denote the resulting four-element vector for each firm-year as $\{Life1, Life2, Life3, Life4\}$. All four exposures are non-negative and are bounded in $[0, 1]$. This scaling is similar to but differs from that used in Hoberg and Maksimovic (2019), who scale by the total number of paragraphs used in all four life cycle queries rather than the total number of paragraphs in the MD&A. We use a different scaling because testing our hypotheses requires that we can compare the influence of each life cycle stage to a null hypothesis of zero influence.[15] We confirm that our four life cycle variables are not jointly multicollinear and hence all four variables can be included in our regressions without econometric concerns.

In addition to including all of the firm-specific life cycle stages in our primary regressions, we also explore the role of peer life cycle stages. To do so, we compute the average life cycle stage of each firm's product market peers using the TNIC-2 industry classification from Hoberg and Phillips (2016). This industry classification is calibrated to be as granular as are two-digit SIC codes. In unreported tests, we find that our results are similar if we use TNIC-3 industries instead of TNIC-2. We focus on the broader set of peers due to the fact that our hypotheses predict that inorganic investment strategies likely interface with both near and more distant peers.

3.3 Firm Disclosure of Trade Secrets versus Patents

We rely on the anchor-phrase method to develop our measure of whether firms disclose their intellectual property in the form of patents or if they instead favor trade secrets and proprietary technologies. This measure was introduced by Hoberg and Maksimovic (2015), who examine the link between financial constraints and opaque information environments. To measure a given firm's loading on trade secret and patent disclosure, we separately identify all paragraphs in a firm's 10-K that contain at least one word from the following lists.

Patent: patent OR patents OR patented

Trade Secret: trade secret OR trade secrets OR trade secrecy OR proprietary technology OR proprietary technologies

[15]The prior study is different and has the objective of testing a conditional Q-model of investments, which requires stages that sum to one for a conditioning partition.

We compute our measure of innovation secrecy by dividing mentions of "trade secrets" by one plus the sum of mentions of "patents" and of "trade secrets". Our innovation secrecy ratio measures each firm's tendency to choose between trade secrets and patents and hence the focal decision regarding whether to disclose its technologies or keep them secret.

3.4 Variables Measuring Disclosure Qualities

As our hypotheses are general, We further consider three additional measures of disclosure secrecy. Our first is firm redaction of information from their 10-K disclosures (Verrecchia and Weber, 2006; Boone, Floros, and Johnson, 2016; Glaeser, 2018). Redaction reflects firm tradeoffs in balancing the need to protect proprietary information while raising capital. Redacting enables managers to keep selective information confidential and helps firms to shield key content from product market competitors. Redaction of material contracts is a common example. Following prior literature, we search for redaction keywords in each firm's 10-K fillings (e.g.,"confidential information, confidential treatment, redacted, CT order," etc.). We classify redacted information using an approach based on Glaeser (2018).[16]

Our second disclosure measure is the readability of financial statements. We measure readability using the Bog Index, a measure capturing plain English attributes[17] and processing costs linked to the type of language used in financial reports (Bonsall, Leone, Miller, and Rennekamp, 2017; Bonsall and Miller, 2017; Chakraborty, Leone, Minutti-Meza, and Phillips, 2019). Related measures include the Fog Index and quantity-based measures such as document length. However, recent research such as Loughran and McDonald (2014) raises concerns that the Fog Index captures word complexity based on syllable counts alone even though the meaning of many of these multisyllabic words (e.g., Company) would be very familiar to even the least

[16]Following Glaeser (2018), we search in the 10-K filing for the mention of "confidential information" "confidential treatment" "redacted" "CT order" "FOIA" "rule 406" or "rule 24b-2."

[17]See SEC (1998) for more details.

sophisticated investors. Bonsall, Leone, Miller, and Rennekamp (2017) argue that quantity-based measures also have limitations as they only capture a single plain English attribute: superfluous words. For example, a majority of the variation in the total file size is caused by the inclusion of content unrelated to the underlying text in the 10-K (e.g., HTML, XML, PDFs). We thus consider the Bog Index derived from a commercial software program, *StyleWriter*, which captures attributes specifically mentioned in the SEC Plain English Handbook including sentence length, passive voice, weak verbs, overused words, complex words, and jargon (SEC, 1998). The Bog Index is constructed using three multifaceted parts capturing sentence-level, word-level and writing-style characteristics of financial reporting readability.

Lastly, we create a competition complaint measure based on 10-K filings following Li, Lundholm, and Minnis (2013) and subsequent extensions in Hoberg, Li, and Phillips (2019). In particular, our first measure is based on a search for competition complaints in financial reports and we use the number of matched paragraphs normalized by the total number of paragraphs in the 10-K to create our base competition measure (*Base Comp*). We then construct two additional measures: *Comp High* and *Comp IP*. The high competition measure (*Comp High*) is the same as the base measures but additionally requires paragraphs to contain one of the words in the following list: (high OR intense OR significant OR face OR faces OR substantial OR significant OR continued OR vigorous OR strong OR aggressive OR fierce OR stiff OR extensive OR severe). Intellectual property competition (*Comp IP*) uses the same approach as *Base Comp* and additionally requires the paragraph to contain both “intellectual” and “property” in the search.

3.5 Pairwise Information Acquisition Based on EDGAR

To further explore how firms’ information acquisition varies at each life cycle stage, we study corporate learning from peers’ disclosures using the server logs of SEC EDGAR database, which record downloads of listed firms’ SEC filings. In particular, we rely on the novel data from Bernard, Blackburne, and Thornock (2019) as the starting point for our pairwise search tests.[18] The authors develop a direct firm-to-firm search measure, *ijsearch*, using IP addresses to identify the corporate identity of downloading agent in the EDGAR database. The approach allows the authors to separate activity of a searching firm i, *Searcher*, from that of the firm j being searched for, *Search Target*. A major advantage of this pairwise database is that it extensively identifies both the firm acquiring the information and the firm whose information is acquired. The authors enhance their ability to identify corporate IP addresses using a *predicted* sample based on expected self-search. The intuition is that EDGAR users often search for their firm's own filings more than they search for other companies' filings.[19]

We limit the pairwise co-search database to only include the 1000 largest firms in each year.[20] We also ensure that these 1000 firms exist in the TNIC database in the corresponding year, thus ensuring they are also covered in the EDGAR database. We then merge the co-search data with the four life cycle variables and compute all cross-term permutations regarding the life cycle exposures of the searching firm and the searched firm. We also winsorize ijsearch variable at the 1% and 99% level within each year[21]. The resulting pairwise search database includes 12,511,748 observations before including additional controls, and it spans a sample period from 2003 to 2016.

3.6 Summary Statistics and Correlations

Table 1 presents summary statistics for our firm-year observations from 1997 to 2017 and Table 2 displays correlation tables for our life cycle variables and log age. We observe that Life1 and pLife1 are negatively associated with firm age, while Life4 and pLife4 are positively associated with firm age. This corroborates that firms generally begin in our sample with a significant fraction of their product portfolio in

[18]We thank authors of Bernard, Blackburne, and Thornock (2019) for sharing the data. Additional details regarding the construction of their EDGAR database are reported in the paper.

[19]See Online Appendix of Bernard, Blackburne, and Thornock (2019).

[20]Tiny firms are too small to have reasonable co-search data and this procedure also makes the database more tractable.

[21]Our analysis is robust to using non-winsorized search data.

the product innovation stage and later have exposure to product discontinuation and eventual delisting. In contrast, Life2 and Life3 have less consistent signs. Hoberg and Maksimovic (2019) suggest that these univariate findings for life cycles are strongly influenced 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. Table 2 also shows that correlations are modest and multicollinearity is unlikely to be a concern.

4 Empirical Results

4.1 Disclosure of Proprietary Information on Innovation

Table 3 tests our four hypotheses by examining the relationship between life cycles and innovation secrecy. In particular, we consider regressions where the dependent variable is the innovation secrecy ratio, which is the number of paragraphs in the 10-K mentioning trade secrets divided by one plus the sum of paragraphs mentioning patents or trade secrets. All models include firm and year fixed effects, as well as a set of standard controls used in the literature. We also cluster standard errors by firm. Our hypotheses predict that Life1 firms will favor opacity (in the context of innovation, they will prefer trade secrets over fully disclosed patents), especially when their peers are also Life1. Life3 firms should favor transparency and thus patents, especially when peers are also Life3. We have no predictions for Life2 or Life4.

Column (1) of Table 3 is a counterfactual model which includes firm age alone as a proxy for firm life cycles. Log age is significantly negative, indicating that firms favor patents over trade secrets as they age. However, this model cannot test our hypotheses, which predict a non-linear pattern related to specific life cycle stages.

Column (2) of Table 3 adds the four life cycle stages of the focal firm. We find that the Life1 coefficient is positive and significant, and Life3 is negative and significant. In contrast, and consistent with results throughout our study, Life2 and Life4 are not consistently significant and have effects that are muted relative to the Life1 and Life3 effects. These results directly support our hypotheses H1 and H3. Column (3) adds the life cycle stages of the peer firms (denoted by pLife1-pLife4). We find that the coefficient estimates on Life1 and Life3 are statistically significant with the expected positive and negative signs, respectively. These results are broadly consistent with early stage firms favoring secrecy to protect their innovative advantage, and Life3 firms favoring disclosure to attract strategic partners. Both results are reinforced when peer firms have analogous Life1 or Life3 exposures.

The results for peer life cycle stages are statistically stronger than are those of the focal firm, suggesting that the stage of one's peers is most important to a firm's disclosure strategy. We also find a negative and significant peer Life2 coefficient in Table 3, suggesting that a focal firm views Life2 peers as being similar to Life3 peers from the innovation disclosure strategy perspective. Finally, Column (4) of Table 3 shows that our results are robust to excluding financials (SIC codes 6000-6999).

Many studies focus on competition, and hence we include competition as a control. We note that our results for the TNIC HHI conform to the general finding in the literature that firms facing more competition (low TNIC HHI) disclose less information about their technologies as they favor trade secrets. As we control for competition, we conclude that life cycles have a distinct impact on disclosure policy. We also note that the life cycle variables are more significant than the competition variable, reinforcing their importance.

One possible concern is whether our innovation secrecy ratio captures the risk factors disclosed in 10-Ks, and that these disclosures might be boiler plate. In unreported results, we compute an alternative measure of patents and trade secrets that omits the risk factor section. Our results are fully robust.

4.2 Redaction to Shield Confidential Information

In this section, we run tests analogous to those in the previous section, except we now focus on the firm's disclosure strategy through the lens of its decision to redact or disclose contractual information about its business operations and activities. Our consideration of redactions follows existing work. For example, Boone, Floros, and Johnson (2016) examine redaction in IPOs and provide evidence supporting our assumption that shielding information from rivals is a primary redaction motive. Other related studies include Tian and Yu (2018), Glaeser (2018), Costello (2013), and Verrecchia and Weber (2006).

Our four hypotheses predict that Life1 firms will redact more aggressively, especially when their peers are also Life1 firms, as doing so should further protect the firm from competitors. This can occur, for example, by increasing the cost of rival emulation, as knowledge of unique contracts can speed a rival's entry and its ability to offer similar contracts. We also predict that Life3 firms will redact less, especially when their peers are also Life3 firms. This should occur because these firms have stable product markets, and their primary goal is to attract more strategic partners. Disclosing more information can be beneficial because it reduces search costs for firms considering acquisitions or related partnerships.

Table 4 reports the results of these tests. We use the anchor-phrase method to build our dependent variable, which is the extent to which a firm redacts content in its 10-K. We calculate this as the count of redaction words in each firm's 10-K using the methods used in Glaeser (2018) and Boone, Floros, and Johnson (2016). This variable is then scaled by the total number of paragraphs in the firm's 10-K. All tests include firm and year fixed effects, and standard errors are clustered by firm. Following prior literature, we include standard controls for all tests. We run the same model specifications used in Table 3.

Column (1) of Table 4 shows our counterfactual model that includes firm age alone, and we find that firms are less likely to redact material contracts when they get older. Column (2) adds our four life cycle variables for focal firms. The coefficient on Life1 is weakly significantly positive at the 10% level and the Life3 coefficient is strongly negative at the 1% level. Columns (3) and (4) add the life cycle variables for the peer firms, and we find even stronger peer-firm results. The coefficient estimates of pLife1 and pLife3 are both significant at the 1% level with signs that reinforce those of the firm-level results. Overall, firms are more inclined to redact portions of their material contracts when they are exposed to Life1, and especially when their peers are in the Life1 stage. This result is intuitive and supports our hypotheses as Life1 firms favor less disclosure and thus more redaction. In contrast, firms are less likely to redact (and disclose more) when they are exposed to Life3, and especially when their peers are exposed to Life3. This is consistent with lowering search costs for potential strategic partners, as suggested by Hoberg and Maksimovic (2019).

We also find that the peer Life4 coefficient is significant and positive, further reinforcing our non-linear predictions. As noted in the previous section, this is consistent with Life4 firms having few growth options and potentially being opportunists in the product market. For example, they might in fact be seen as a threat to some firms in earlier stages, who might be worried about opportunistic risk taking by Life4 firms. Hoberg and Maksimovic (2019) show some evidence of such opportunism by Life4 firms in the financial crisis.

4.3 Information Processing Cost and Readability

Recent studies have shown that the complexity of financial filings, and hence information processing costs, has increased over the last two decades (Dyer, Lang and, Stice-Lawrence, 2017; Li, 2008). Although quantitative disclosures generally have low processing costs (Liberti and Petersen, 2019), Blankespoor, deHaan, and Marinovic (2019) suggest that poor readability specifically can be a non-trivial component of disclosure processing costs. In our context, low readability is analogous to providing less disclosure as a reader is likely to take less away from an unreadable document just as they would take less away from a document with less disclosure. Hence we predict that Life1 (Life3) firms will favor less (more) readable disclosures.

Our dependent variable in Table 5 is the Bog Index based on Bonsall, Leone, Miller, and Rennekamp (2017). A high bog index indicates a less readable document. Column (1) of Table 5 shows that 10-K readability improves with firm age. Our main result in Column (2) is that Life1 firms have less readable 10-Ks whereas Life3 firm 10-Ks are more readable. We also find that Life2 firms tend to provide less readable filings although in a less extreme way relative to Life1 firms. Finally, consistent with our earlier results, Life4 firms have results that contrast with those of Life3 firms, highlighting the non-linearity with the life cycle, as their filings are less readable.

Columns (3) and (4) of Table 5 add the peer firm life cycle exposures. The results mirror those in Column (2), especially for our central Life1 and Life3 predictions. Not surprisingly given their ambiguous predictions, Life2 and Life4 are not significant for the peer firm perspective. These findings support our key hypotheses and are novel given the literature, which has not yet studied the dynamics of readability based on firm life cycle stages.

4.4 Competition Complaints in the SEC Filings

In this section, we examine ex-post complaints about competition for firms at different life cycle stages. This test is motivated by our central thesis that product life cycles and competition are distinct economic forces, but they should also interact in predictable non-linear ways. Because we control for competition in our models, it already follows that our life cycle results are unique. Yet we furthermore note that our hypotheses also predict that these two forces might have important nonlinear interactions. For example, our predictions for Life1 hinge upon competition being a particularly important factor for firms in this early stage of the life cycle and their peers. On the other hand, our predictions for Life3 do not rely on competition being a relevant force at all, as our predictions arise from incentives relating to inorganic growth opportunities and reducing search costs.

The dependent variable in Table 6 is the number of paragraphs in which the firm mentions competition (or any word with the same word root "compete") divided by the total number of paragraphs in the 10-K, all scaled by 1000 for ease of interpretation. The table confirms our main prediction that Life1 firms complain about competition far more than firms in any other life cycle stage do. The t-statistic for Life1 of the focal firm exceeds 6.0 in all specifications. In contrast, we also confirm that Life3 firms are less focused on competition although the t-statistics are substantially smaller and are in the range between 2.0 and 3.0 depending on the specification. The other focal firm life cycle stages are not significant. These results provide rather unique and specific support for the mechanisms we propose are at play when we motivated our main hypotheses in Section 2. Regarding peer effects these also support our central hypothesis as we again see sharply positive and significant results for peer Life1 and negative and significant for peer Life3. When a firm has peers that are particularly exposed to Life1, it becomes especially concerned about competition, as such firms are in search of a position in the market and pose significant competitive threats. In contrast, peers that are exposed to Life3 pose little competitive threat, as these firms are more interested in complementary relationships. Hence we observe less focus on competition in these cases. In our online appendix, we show that these results are also robust to alternative measures of competition that (A) additionally condition on the discussion being about innovation and competition in tandem or (B) that specifically mention that competition is high. We also show that our findings in Section 4 are not driven by financial constraints.[22]

4.5 Economic Magnitudes

In this section, we examine the economic magnitude of our baseline disclosure results. Our main result is that disclosure policies are polar opposites across the product life cycle stages Life1 and Life3. Hence we perform quintile sorts annually using the difference between Life1 and Life3 (Life1-Life3). In Panel A of Table 7, we report the

[22] Please see Online Appendix Table A6.

averages of each disclosure policy for the high and low (Life1-Life3) quintile as well as the inter-quintile range and its significance level. We conduct analogous quintile sorts using the peer life cycle exposures (pLife1-pLife3) in Panel B. To make the reported magnitudes more intuitive, we standardize all of our continuous disclosure variables before reporting their quintile averages. Hence the inter-quartile range can be interpreted as the number of standard deviations the given disclosure variable shifts when moving from the first to the fifth (Life1-Life3) quintile. To further improve intuition, two of our variables (redaction and technology competition complaints) have a natural representation as dummy variables, and we also report the average of these dummies across the quintiles.

Panel A illustrates that our findings for own-firm product life cycle exposures are economically large. For all disclosure variables, firms with high Life1 vs. Life3 (High Quintile) disclose substantially less than firms with low Life1 vs. Life3 (Low Quintile). All continuous disclosure variables have an inter-quintile range of one-third to one-half of one standard deviation. Regarding the two indicator variables, only 30.3% of low quintile firms (Life3-focused) are redactors whereas 54.6% of high quintile firms (Life1-focused) are redactors. Analogously, only 56.0% of low quintile firms discuss technology competition complaints compared to 81.5% for high quintile firms. These magnitudes are large indicating first-order relevance for the product life cycle. The results for peer-firm life cycle effects in Panel B are even larger, with most continuous variables experiencing shifts of more than one-half of one standard deviation across the quintiles, and the two dummies seeing even larger wedges.

4.6 Firm Age, Rigidities, and Product Life Cycles

Our approach thus far has been to focus on the product life cycle (PLC) while controlling for the firm life cycle (FLC), measured using firm age. Our analysis shows that they each have distinct and economicaly significant impact on disclosure policies. In this section, we test the hypothesis that the PLC and the FLC also interact with one another. These tests are motivated by our baseline hypotheses, coupled with the conclusions in Loderer, Stulz and Waelchli (2016) that firms become more rigid as the FLC progresses, and therefore are less able to exercise their growth options.

Our extended hypothesis is that increases in firm rigidity that come with aging via the FLC should also moderates the firm's ability to implement its optimal PLC disclosure policies. In particular, as firms age, their disclosure policies might become more institutionalized as firms become less adept at customizing their disclosure policies to optimize the PLC. We thus predict that younger Life1 firms will reduce disclosure more than older and more rigid Life1 firms. Analogously, younger Life3 firms will use their flexibility to increase their disclosure more than older Life3 firms. Because we reported earlier that a firm's exposure to the PLC and the FLC are only modestly correlated, there is ample power to test these hypotheses using interactions between our product life cycle measures and firm age.

We add interactions between our text-based PLC measures and firm age to our baseline regressions and report the results in Table 8. To improve interpretation and reduce variance inflation from interactions, we first standardize log age to have zero mean and unit standard deviation.[23] The regression results strongly support our predictions for innovative secrecy and our redaction variable. In particular, Life1 and Life3 interactions with standardized log age are significant and have signs that are opposite the baseline effects for the Life1 and Life3 levels. For example, for innovative secrecy, the positive and significant Life1 variable indicates our earlier main result that Life1 firms are more secretive. The negative and significant coefficient for Life1 x log age coefficient indicates that the our baseline result is even stronger for younger firms (which have negative values for standardized log firm age). In contrast, as firms age, the level effect and the interaction offset, and these firms become less adept at modifying their disclosure in favor of secrecy. These results both support our central PLC thesis, but also support our extension of Loderer, Stulz and Waelchli (2016) to the novel setting of disclosure.

[23]Our results are similar if we skip this step, although variance inflation factors for some variables exceed the cautionary level of 10. Standardizing log age reduces all variance inflation factors to less then 5, which indicates no concerns.

Table 8 also shows analogous results for Life3. Our baseline result is that Life3 firms favor less secretive innovation disclosure. The positive and significant Life3 x log age coefficient (significant at the 10% level) shows that this result is also weakly stronger for younger firms. In particular, young life3 firms are especially likely to increase transparency, but as firms age, they become less reactive. These results also support both our PLC hypotheses and illustrate an additional role for the FLC in line with Loderer, Stulz and Waelchli (2016).

The remaining columns in Table 8 show that our interaction results are even stronger for our redaction variable. Our main result that Life1 firms redact more and Life3 firms redact less is highly robust, but we also find that younger firms appear to be more flexible in customizing disclosure policies as both results become weaker (significant at the 1% level) as firms age. In contrast, although our PLC results remain strong for the Bog index and the competition variable, we do not find analogous interactions between the PLC and the FLC for these two variables. This finding reinforces the independent relevance of the PLC and FLC effects, as the level effects remain significant for both variables. Finally, although we do not report them to conserve space, we also note that interacting the peer life cycle effects with firm age produces results similar to those for the focal firm life cycle variables.

5 Sender and Receiver Tests

Our thesis predicts that disclosure policies are chosen not only based on the focal firm's product life cycle (PLC) stage, but also that of its peers. At its core, the logic is that the focal firm is a "sender" when it chooses its disclosure policies, and its peers are "receivers". The optimal disclosure policy of the sender internalizes the consequences of the receiver's actions. We consider two tests of this refined aspect of our hypothesis, which predicts that the joint properties of the firm and its peers (pairwise attributes) should matter over and above the individual parts.

5.1 Focal Firm and Peer Firm Interactive Effects

Our paper's findings should be strongest in two instances. The first is when both the focal firm and its peers are highly exposed to Life1. Maksimovic and Pichler (2001) show that, during the product development stage, the focal firm is vulnerable to preemption by competitors. Hence the firm benefits from limiting disclosures as rivals in the same stage can exploit unrealized technology or plans. Consistent with Boot and Vladimirov (2020), the second is when both the focal firm and its peers are in the mature stage Life3, as synergistic cooperation is more likely.

These channels specifically predict that interaction terms between focal firm PLC stages and peer PLC stages should matter. Table 9 explores these expanded regression models, and the results support the conclusion that life-stage matches between the PLC of the focal firm and its peers indeed matter. As predicted, when both the focal firm and its peers are more focused on Life1 activities, the level of disclosure is reduced even further. When both parties are jointly in the mature Life3 stage, disclosure increases further.

These interactive results are consistent across our measures of disclosure quality. When firms and their peers are jointly exposed to Life1 (Life3), we see more (less) secretive innovation, redaction, and unclear writing as indicated by the Bog Index. Column (7) of Table 9 further confirms our prediction that the focal firm's concerns about competitive threats follow a similar pattern, and are higher when both it and its peers are focused on Life1, and lower when they are both focused on Life3.

Table 9 shows that, for information secrecy and redaction, the characteristics of the focal firm alone are not sufficient to explain its disclosures when the interactions are added. The strong interaction results are further consistent with explanations in which the sender and receiver jointly matter, as is the case for our proposed thesis.

5.2 Pairwise Search and Product Life Cycles

In this section, we directly test the sender versus receiver hypothesis by examining the actual downloads of the disclosed EDGAR filings across specific firm-pairs with different PLC exposures. To do so, we follow Bernard, Blackburne, and Thornock (2019) who use firm IP addresses to track which firms are downloading the disclosures of peer firms using the SEC EDGAR server logs.

Our hypotheses make highly specialized predictions for which firms will download the filings of which other firms. First, we predict that Life1 firms will aggressively download the filings of other Life1 firms, as doing so could yield a competitive advantage about product market placements and useful technologies. Firms in Life1 have particularly strong incentives to gather this information given they are actively searching for markets, and major decisions will be difficult to reverse if they are poorly researched. We also predict that Life3 firms will aggressively download the filings of other Life3 firms. For these firms, their primary source of growth rests with attracting partners to fuel inorganic growth, and developing and optimizing synergistic alliances between firms requires extensive ex-ante search. In contrast, our hypotheses would predict less downloading between Life2-pairs or Life4-pairs.

Our pairwise database is large and has high power, which also allows us to examine whether firms in a given life stage tend to search (or not) firms in non-matching life stages (for example, whether Life3 firms aggressively download the filings of Life1 firms). Although our predictions regarding these asymmetric pairs are less stark than our above symmetric-pair predictions, results in Hoberg and Maksimovic (2019) would suggest that Life3 firms take a broader perspective on who they search for alliances than do Life1 firms. In particular, that study finds some elevated sensitivity to merger activity not only for Life3 firms, but also to a lesser extent for Life4 firms. The study also suggests that the Life1 stage is unique as this is the only stage where specific products might not yet be on the market. Hence we would generally predict higher downloading when one member of a pair of firms is a Life3 firm and the other is in Life2 or Life4, and we would predict less downloading when one firm is a Life1 firm and the other is not. The most unlikely pair to observe downloading might be Life1 and Life3 pairs, as these firms have more definitively asymmetric objectives according to our theory and should benefit less from one another's disclosures.

We test these hypotheses in Table 10, where the dependent variable is the number of times an employee in firm i downloads the filings of firm j in the given year from the SEC's EDGAR database. This measure indicates the intensity of downloading of filings that is unique to the given pair. Our key independent variables of interest are the interacted life cycle stages of the two firms i and j. For example, the variable "Life1 Search Life1" is a pairwise variable equal to the amount of Life1 exposure firm i has multiplied by the amount of Life1 exposure firm j has. All PLC variables are analogously defined. We additionally include firm-pair and year fixed effects, and cluster standard errors by firm. As the data becomes sparse for very small firm-pairs, we only include the 1000 largest firms based on assets in our sample in each year.

The results in Table 10 strongly support our core predictions. Most important, the only symmetric pairs that are positive and significant are "Life1 Search Life1" and "Life3 Search Life3". These positive and significant coefficients indicate that disclosure is highly focal for firms in these two stages, and in both cases, it is related to the fact that peers in a similar stage have strong incentives to search one another's filings for symmetric reasons. However, similar results do not obtain for "Life2 Search Life2", which is negative or "Life4 Search Life4," which is not significant. Overall, these results support the most core assumption made regarding our hypothesis and its microfoundation noted in Section 2.

Regarding our peripheral predictions for asymmetric life cycle pairs, we also find support for these more nuanced predictions. Any coefficient for a pair containing Life1 and a different life cycle stage such as "Life1 Search Life3" is negative and most are significant. In contrast asymmetric pairs containing Life3 and either Life2 or Life4 (such as "Life3 Search Life2") are positive and significant. These findings suggest that Life3 firms cast a wider net when searching for synergistic peers, but they avoid Life1 firms as they do not yet have products placed in the market.

We also note that Life3 firms downloading the filings of Life2 firms, and vice-a-versa has an interesting and reinforcing microfoundation that has roots in a first mover advantage. For example, Life2 firms are likely to become the next Life3 firms. Hence it is sensible for current Life3 firms to search for inorganic growth opportunities with current Life2 firms even as these firms are working to stabilize their production costs. By doing so, they are first movers and can realize gains before other Life3 firms might act. Downloading activity between Life3 and Life4 pairs is also sensible as one member of this pair is generally a buyer of assets (the Life3 firm) and the other is generally a seller (the Life4 firm).

Our control variables also have expected signs, which helps to further validate the empirical framework of Bernard, Blackburne, and Thornock (2019), which we adopt here. For example, a higher TNIC similarity score very strongly predicts additional downloading between the given pair of firms. We have also included both firm-pair and year fixed effects. Firm-pair effects absorb time-invariant sources of unobservable heterogeneity unique to each firm pair.

6 Sectoral Patent Depreciation Waves

A central theme in our hypotheses is that firms consider how other firms in related markets potentially use their disclosure. These related firms could be competitors (relevant to Life1 firms) or firms that offer complementarities (relevant to Life3 firms). Our main analyses test equilibrium predictions and are not aimed at establishing causal inference. In this section, we examine a novel and plausibly exogenous shock to the entry incentives of firms into a given firm's sector. Under our central hypotheses, this shock will induce Life1 firms to reduce disclosure even further, as the potential entrants will be seen as competitive threats to their not-yet-established market positions. On the other hand, we predict that this should should induce Life3 firms to disclose even more, as the potential entrants will primarily be seen as candidates for attracting new synergistic inorganic relationships.

We propose a novel instrument that is new to the literature - sectoral patent depreciation waves. Intuitively, we want to identify sectors facing major slowdowns in their path of innovation. In such cases, earlier and highly important waves of protected IP would be experiencing rapid depreciation, and recent innovations are not intense enough to replenish the depreciation in protected intellectual property. Such waves of IP protection losses should reduce barriers to entry, and we expect (A) more new entrants and (B) existing firms in related markets might expand their product offerings to more directly compete in the focal market. Our hypothesis suggests that such a shock to expected entry in a broad sector will lead Life1 firms to reduce all forms of disclosure, and lead Life3 firms to increase disclosure to attract the new entrants to participate in inorganic alliances. Because we focus on broad sector-wide waves of depreciation, because we construct our measures using deeply lagged data, and because we include numerous controls including firm fixed effects, our measures of depreciation waves are plausibly exogenous shifters of entry incentives.

We measure innovative activity at the sector level over long, and deeply lagged windows. As patents are typically valid for 20 years in our sample, we first form two windows: an "early" window that includes years [t-11 to t-19] and a "late" window that includes years [t-2 to t-10]. The additional two year lag in the late window is to ensure both periods are deeply lagged. To reinforce this objective, and to reduce patent truncation bias (see Lerner and Seru (2020)), we also measure these windows relative to the patent grant date (although our results are very similar if we use the application date). Our wave measure aggregates patenting activity over entire sectors over long ten year windows, and hence our measure captures a wide swath of innovation, ensuring it should be economically important. Figure 1 visualizes the construction of the patent depreciation waves.

We obtain firm-year patent data from Kogan et al (2017) (KPSS), which is mapped to public firm permnos. We first sum the total number of patents granted to public firms in each year in each sector (we consider two-digit and three-digit SIC), and divide this total by the total firm value of all firms in the sector in the given year.[24] We then average the resulting yearly patent/value ratios over all years in the early and late windows for each sector. This aggregation approach is naturally value weighed and avoids division by zero or near-zero denominators. Our key IP depreciation waves variable is then:

PatDepWave = Patent-to-value Ratio (early) - Patent-to-value Ratio (late)

We construct separate measures of PatDepWave using sectors defined based on SIC-2 industries, SIC-3 industries, and an "outer peers" classification (SIC-2o3 hereafter). For a focal SIC-3 industry, outer peers are the other nearby SIC-3 industries that are in the same SIC-2 industry as the focal SIC-3 industry. Figure 2 provides a simple visualization of how these sector-groups are formed. Before running our models, we de-mean the patent depreciation wave variables to reduce multicollinearity and improve interpretation. Our results are robust to using a specification where we discard patents with a market value below the median in the given year (patent valuations are based on stock announcement returns as in KPSS). Our results are also robust to using 7 year windows for the early and late periods.

6.1 Patent Expiration Waves and Disclosure Strategies

Tables 11 and 12 report our main results regarding protected IP depreciation waves and disclosures. We regress all disclosure measures (innovation secrecy, information redaction, disclosure readability and IP competition complaints) on the life cycle stages of the firm, their interactions with patent depreciation waves, all controls, and firm and time fixed effects. All standard errors are clustered by firm.

Columns (1) to (3) in Table 11 report the results for innovation secrecy using three different levels of industry granularity. We find that Life1 firms become more secretive regarding their intellectual property when sector-level IP rapidly depreciates and entry threats increase. In contrast, Life3 firms become more transparent and focus on patents, consistent with attracting more strategic partners. These results

[24] Firm value is assets minus book equity plus market equity.

are consistently significant at the 1% level when sectors are defined narrowly using SIC-3 industries or defined broadly using SIC-2 industries, or using the broad outer-peers SIC-2o3. These results for the innovation secrecy variable support our central thesis that increased entry in the sector increases secrecy incentives for Life1 firms but increases transparency incentives for mature Life3 firms.

Columns (4) to (6) of Table 11 document analogous results for disclosure redaction. Life1 firms redact more and thus become more secretive during patent depreciation waves for all three levels of granularity. Life3 firms redact less, especially for broader industry classifications (SIC-2 and outer-peers SIC-2o3). These findings support our proposed link to inorganic growth opportunities, and also our more refined hypothesis that inorganic growth opportunities are most likely to lie with more distant and thus complementary peers rather than with the closest peers that are more competitive.

Columns (1) to (3) in Table 12 display the results for the Bog Index. All three tests are again supportive of our central hypotheses. Life1 firms lower the readability of their 10-Ks following the shock, and Life3 firms improve their readability. As above, the Life3 results for the broader industry classifications (SIC-2 and outer-peers SIC-2o3) are particularly strong.

Columns (4) to (6) of Table 12 report results for IP-related competition complaints using the same three granularities. For the broader granularities (SIC-2 and SIC-2o3), we find that the key depreciation waves interaction term is positive and statistically significant for Life1 firms and negative and significant for Life3 firms, all at the 1% level of significance. Consistent with our above findings, the results are weaker and become insignificant when the shock is defined more narrowly at the SIC-3 granularity. These results support a key validating assumption of our depreciation waves variable. In particular, our interpretation is that this kind of shock increases entry incentives and Life1 firms will view the entrants as competitive threats, and the Life3 firms view them as new potential inorganic alliance partners. The results for IP-competition validate this interpretation as Life1 (Life3) firms indeed do complain more (less) about competition specifically relating to their IP.

In Online Appendix Table A2 and A3, we report robustness tests where we compute patent depreciation waves only using patents with KPSS market values that are above the median in their given year. The test thus focuses on high-value patents only. The table shows that our results are fully robust.

7 Strategic Disclosure Quality in Conference Calls

The majority of public firms hold regular conference calls with investors and equity analysts, in which management discusses firm's past performance and future prospects. Conference calls have been regarded as an ubiquitous avenue for information dissemination and corporate disclosures (Matsumoto et al., 2011). We use textual analysis of earnings conference-call transcripts to construct firm-level measures of the disclosure quality in the management presentations. We focus on the opening statements, as it is expected that executives (the firm's CEO and CFO, or other key personnel) are more likely to choose topics they wish to disclose or strategically emphasize in the presentation than they would in Q&A sessions (Bourveau et al, 2020, Hassan et al, 2019). Recent studies have established that earnings conference calls facilitate large information transfers to peer firms (Brochet et al., 2018, Kimbrough and Louis, 2011). It has also been shown that managers strategically manage the flow of information in such events (Hollandert al. 2010, Mayew 2008). Investor relations advisory and strategic communications practitioners also suggest that firms should "tune in to what your competitors are reporting and discussing (in conference calls)."[25]. Yet there is still a dearth of research on the potential mechanisms of information transfers (Brochet et al., 2018).

The managerial presentation section of the conference call is an ideal setting to test our hypothesis because the presentation is well-prepared, scripted, and firms have significant latitude regarding its content.[26] We thus argue that the product life

[25]http://westwicke.com/2013/01/best-practices-for-earnings-call-preparation/

[26]https://deloitte.wsj.com/cfo/2017/10/09/preparing-for-the-first-earnings-call-lessons-for-new-

cycle should play an important role governing the information quality of the presentation. Under our central thesis, Life3 firms will produce higher quality presentations to facilitate inorganic opportunities. In contrast, Life1 firms are concerned about competitive threats and will provide less informative presentations.

Following Hanley and Hoberg (2010), we introduce a new measure to quantify the informativeness of earnings conference calls. We compute a firm-year disclosure quality metric as one minus the cosine similarity between a firm's earnings call presentation and the average text of that of its SIC-2 peers in the same year (we exclude the firm itself from the industry average used in this calculation):

$$\boldsymbol{ConfCallDisQuality} = 1 \text{ - } CosineSimilarity\{Presentation_{firm}, Presentation_{industry}\}$$

This measure allows us to explore whether a firm's management presentation has more informative content than its average industry peers. This measure does not rely on any specific word lists or dictionaries. We collect the transcripts of all earnings conference calls between 2002 and 2017. Transcripts with fewer than 250 words and firms with fewer than 25 peers are excluded. When a firm has more than one conference call in a given year, we aggregate all presentations into one aggregated document for this calculation, thus using all of the available data over the period.

Table 13 reports our baseline tests using earnings-call disclosure quality as the dependent variable. Our main results in Column (1) show that Life1 firms decrease their disclosure informativeness whereas Life3 firms provide more information content in their earnings calls. Columns (2) and (3) add the peer life cycle exposures (pLife1-pLife4) to the tests. For own-firm product life stages (Life1-Life4), we consistently find strong negative results for Life1 firms and strong positive results for Life3 firms with controls and firm fixed effects included. This is in line with our central hypothesis that Life3 firms have incentives to reduce search costs for inorganic growth opportunities whereas Life1 firms favor secrecy. In addition, we find that the Life3 peer coefficient is positive and statistically significant. The peer Life1 variable has a negative coefficient but is not significant at conventional levels. This is likely

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due to the fact that our sample of conference call transcripts is smaller than that of our baseline tests. Overall, the results further support our thesis that firms in the early stage of product life cycles favor secrecy to mitigate competitive threats, and mature Life3 firms increase disclosures to attract strategic partners.

As we did for our baseline tests, we next examine the impact of patent depreciation shocks on conference call disclosure quality. In Table 14, we regress this variable on our product life cycle variables and their interactions with patent depreciation waves. We include all controls from our baseline model and also include firm and time fixed effects. Consistent with our expectations, we observe in Columns (1)-(3) that early stage Life1 firms provide less informative earnings-call presentations, and Life3 firms become more transparent following patent depreciation waves. These findings are robust to using the narrowly defined SIC-2 and SIC-3 industries or the outer-peers SIC-2o3 specification.

8 Conclusion

We show that a firm's product's life-cycle stages shape its disclosure policies. The foundation for this relationship likely lies in the investment strategies of firms in different life cycle stages. Firms exposed to the early stage of the product life cycle have inward focused organic growth strategies. To maintain the advantage of stealth, these firms benefit most from a low disclosure regime. In contrast, firms with mature products have outward focused inorganic growth strategies. These firms benefit from high disclosure as it can reduce search costs and attract a larger number of synergistic relationships. Using a text-based life cycle model, we find strong support for these predictions across three disclosure policies: innovation disclosure in the form of patents versus undisclosed trade secrets, contractual disclosures in the form of less 10-K redactions, and disclosure that is more readable. These findings are reinforced by a quasi natural experiment based on rapidly depreciating intellectual property where our predictions are particularly strong.

Additionally, we find a strong link between the product life cycle (our primary focus) and the firm life cycle modeled using firm age: younger firms are significantly more agile in adjusting their disclosures either to favor secrecy or transparency as indicated by their unique product life cycle incentives. This supports the view in the existing literature that firms become more rigid as they age, creating strong interactions between the product life cycle and the firm life cycle.

We propose and find that the market structure around a firm is also crucial in understanding life cycle effects. When a firm's product market peers are in the early product development stage, the focal firm favors a more secretive disclosure strategy. In contrast, when peers are in the mature life cycle stage, and are also searching for inorganic growth opportunities such as acquisitions and partnerships, the focal firm favors a more transparent disclosure strategy. These results are reinforced by tests based on interaction terms, which show that the characteristics of both the discloser and the intended receiver of the disclosure jointly matter. Intuitively, the returns to disclosing for a mature Life3 firm seeking synergistic alliances are magnified when it is in a sector with many other Life3 firms seeking the same objective. To further test that the sender and receiver both matter, we adopt the novel framework of Bernard, Blackburne, and Thornock (2019) and analyze the intensity at which employees in one firm download the SEC EDGAR filings of peer firms. Consistent with our hypothesis, we find that both early and mature stage firms download the filings of their same-stage peer firms with a significantly higher intensity. Similar findings do not obtain for other life stages.

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Table 1: Summary Statistics

Summary statistics are reported for our sample based on annual firm observations from 1998 to 2017. The product life cycle variables (Life1-Life4 and pLife1-pLife4) are based on textual analysis of 10-K statements using anchor-phrase queries in each year (Please see section 3 for details). 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). Life1-Life4 measure focal firms. pLife1-pLife4 measure peer firms based on TNIC-2 granularity. We have scaled the competition complaint and redaction measures by 1000. All variables are described in detail in Section 3.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	N	mean	p50	sd	p25	p75
Life1	97,311	0.281	0.158	0.306	0.0664	0.357
Life2	97,311	0.347	0.285	0.259	0.173	0.435
Life3	97,311	0.294	0.186	0.296	0.0968	0.339
Life4	97,311	0.0807	0.0164	0.185	0	0.0673
pLife1	93,777	0.298	0.283	0.134	0.192	0.390
pLife2	93,777	0.351	0.343	0.107	0.278	0.417
pLife3	93,777	0.306	0.291	0.117	0.216	0.388
pLife4	93,777	0.0794	0.0732	0.0429	0.0496	0.101
Log Age	97,311	2.592	2.565	0.821	1.946	3.178
Innovation Secrecy	97,311	0.114	0	0.172	0	0.200
Redaction	97,311	0.892	0	2.219	0	1.271
Bog Index	93,754	83.90	84	7.548	79	89
BaseComp	97,311	16.22	14.37	10.92	9.560	20.83
CompIP	97,311	3.639	1.595	5.661	0	5.658
CompHigh	97,311	5.998	4.944	7.119	2.548	8.130
Log 10-K Size	97,311	6.405	6.474	0.570	6.091	6.795
Log Assets	96,931	6.010	6.062	2.272	4.434	7.540
TNIC HHI	93,900	0.265	0.148	0.272	0.0736	0.353
Tobin's Q	95,647	1.693	1.079	2.094	0.681	1.851

Table 2: Correlation Table (Life Cycle Variables)

Correlations for the product life cycle variables are reported for our sample based on annual firm observations from 1998 to 2017. The product life cycle variables (Life1-Life4 and pLife1-pLife4) are based on textual analysis of 10-K statements using anchor-phrase queries in each year (Please see section 3 for details). 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). Life1-Life4 measure focal firms. pLife1-pLife4 measure peer firms based on TNIC-2 granularity. All variables are described in detail in Section 3.

Variables	Life1	Life2	Life3	Life4	pLife1	pLife2	pLife3	pLife4	Log Age
Life1	1.000								
Life2	0.583	1.000							
Life3	0.795	0.604	1.000						
Life4	0.399	0.443	0.415	1.000					
pLife1	0.394	0.107	0.254	0.055	1.000				
pLife2	0.109	0.382	0.141	0.091	0.327	1.000			
pLife3	0.263	0.144	0.358	0.062	0.705	0.425	1.000		
pLife4	0.104	0.162	0.108	0.147	0.317	0.473	0.348	1.000	
Log Age	-0.020	0.106	0.036	0.144	-0.226	0.082	-0.152	0.100	1.000

Table 3: Firm Life Cycles of Innovation Secrecy

The table reports firm-year panel estimates for our sample of annual firm observations. An observation is one firm in one year. The dependent variable is an innovation secrecy variable, which is calculated by dividing mentions of "trade secrets" by one plus the sum of the mentions of "patents" and of "trade secrets" in the filings. We have scaled the innovation secrecy variables by 100. The product life cycle variables (Life1-Life4 and pLife1-pLife4) are based on textual analysis of 10-K statements using anchor-phrase queries in each year (Please see section 3 for details). Column (1) is based on firm age and other key control variables. Column (2) and (3) report results for a product life cycle versus innovation secrecy model. Column (2) is based on the four life cycle variables for focal firms (Life1-Life4). Column (3) is based on the eight life cycle variables (Life1-Life4 for focal firms; pLife1-pLife4 for peer firms based on TNIC-2 granularity). Column (4) shows the test result of eight life cycles that excludes financials (SIC codes 6000-6999) from the sample. All columns include firm and year fixed effects, and standard errors are clustered by firm. Key controls are included for all tests. All RHS variables are standardized. *t*-statistics are in parentheses.

	(1)	(2)	(3)	(4)
	Full Sample	Full Sample	Full Sample	Exclude Financials
VARIABLES	Innovation Secrecy	Innovation Secrecy	Innovation Secrecy	Innovation Secrecy
	x 100	x 100	x 100	x 100
Life1		0.385***	0.319**	0.541***
		(2.699)	(2.240)	(2.817)
Life2		-0.0710	-0.0362	-0.00323
		(-0.653)	(-0.333)	(-0.0217)
Life3		-0.344**	-0.307**	-0.431**
		(-2.509)	(-2.241)	(-2.280)
Life4		0.123*	0.114	0.164*
		(1.697)	(1.567)	(1.938)
pLife1			1.288***	1.291***
			(5.203)	(4.883)
pLife2			-0.830***	-0.666***
			(-5.020)	(-3.701)
pLife3			-0.823***	-1.180***
			(-3.726)	(-4.762)
pLife4			-0.0446	0.0659
			(-0.682)	(0.933)
Log Age	-2.264***	-2.396***	-2.300***	-2.454***
	(-7.907)	(-7.008)	(-6.770)	(-5.371)
Log 10-K Size	0.899***	0.847***	0.805***	0.899***
	(7.009)	(6.044)	(5.753)	(5.177)
Log Assets	0.836**	0.835**	0.787**	0.532
	(2.524)	(2.271)	(2.141)	(1.339)
TNIC HHI	-0.600***	-0.512***	-0.458***	-0.585***
	(-6.078)	(-4.854)	(-4.369)	(-5.285)
Tobin's Q	0.284***	0.243**	0.190*	0.216**
	(3.446)	(2.452)	(1.916)	(2.107)
Observations	107,195	93,178	93,039	71,992
R^2	0.765	0.770	0.770	0.766
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Redaction to Shield Confidential Information

The table reports firm-year panel estimates for our sample of annual firm observations. An observation is one firm in one year. The dependent variable is a redaction variable, which is calculated as the count of redaction words in 10-K filings based on Glaeser (2018) and Boone, Floros, and Johnson (2016). We have scaled the redaction variables by 1000. The product life cycle variables (Life1-Life4 and pLife1-pLife4) are based on textual analysis of 10-K statements using anchor-phrase queries in each year (Please see section 3 for details). Column (1) is based on firm age and other key control variables. Column (2) and (3) report results for a product life cycle versus redaction model. Column (2) is based on the four life cycle variables for focal firms (Life1-Life4). Column (3) is based on the eight life cycle variables (Life1-Life4 for focal firms; pLife1-pLife4 for peer firms based on TNIC-2 granularity). Column (4) shows the test result of eight life cycles that excludes financials (SIC codes 6000-6999) from the sample. All columns include firm and year fixed effects, and standard errors are clustered by firm. Key controls are included for all tests. All RHS variables are standardized. *t*-statistics are in parentheses.

	(1)	(2)	(3)	(4)
	Full Sample	Full Sample	Full Sample	Exclude Financials
VARIABLES	Redaction x 1000	Redaction x 1000	Redaction x 1000	Redaction x 1000
Life1		0.0830*	0.0688	0.0837
		(1.891)	(1.560)	(1.346)
Life2		0.0324	0.0299	0.0255
		(1.403)	(1.303)	(0.827)
Life3		-0.0887***	-0.0679***	-0.0845**
		(-3.550)	(-2.720)	(-2.491)
Life4		0.00416	-0.000208	-0.000120
		(0.365)	(-0.0185)	(-0.00851)
pLife1			0.169***	0.131***
			(4.792)	(3.462)
pLife2			-0.0228	-0.0335
			(-1.058)	(-1.465)
pLife3			-0.252***	-0.209***
			(-6.533)	(-4.938)
pLife4			0.0586***	0.0586***
			(5.484)	(5.106)
Log Age	-0.225***	-0.171***	-0.157***	-0.218***
	(-5.211)	(-3.685)	(-3.367)	(-3.309)
Log 10-K Size	-0.194***	-0.133***	-0.142***	-0.174***
	(-2.606)	(-3.381)	(-3.586)	(-3.231)
Log Assets	0.0756	0.0531	0.0523	0.0422
	(1.524)	(1.216)	(1.202)	(0.847)
TNIC HHI	-0.0602**	-0.0509*	-0.0492*	-0.0550*
	(-2.438)	(-1.747)	(-1.680)	(-1.667)
Tobin's Q	0.0674***	0.0734***	0.0649***	0.0652**
	(3.315)	(2.889)	(2.586)	(2.365)
Observations	107,195	93,178	93,039	71,992
R^2	0.578	0.594	0.595	0.593
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Financial Reporting Readability Measured by Bog Index

The table reports firm-year panel estimates for our sample of annual firm observations. An observation is one firm in one year. The dependent variable Bog Index is a plain English measure of financial reporting readability based on Bonsall, Leone, Miller, and Rennekamp, (2017), which is a multifaceted index designed to capture a broad set of plain English attributes. The product life cycle variables (Life1-Life4 and pLife1-pLife4) are based on textual analysis of 10-K statements using anchor-phrase queries in each year (Please see section 3 for details). Column (1) is based on firm age and other key control variables. Column (2) and (3) report results for a product life cycle versus readability model. Column (2) is based on the four life cycle variables for focal firms (Life1-Life4). Column (3) is based on the eight life cycle variables (Life1-Life4 for focal firms; pLife1-pLife4 for peer firms based on TNIC-2 granularity). Column (4) shows the test result of eight life cycles that excludes financials (SIC codes 6000-6999) from the sample. All columns include firm and year fixed effects, and standard errors are clustered by firm. Key controls are included for all tests. All RHS variables are standardized. *t*-statistics are in parentheses.

	(1)	(2)	(3)	(4)
	Full Sample	Full Sample	Full Sample	Exclude Financials
VARIABLES	Bog Index	Bog Index	Bog Index	Bog Index
Life1		0.339***	0.286***	0.423***
		(4.903)	(4.200)	(5.207)
Life2		0.149***	0.139***	0.144**
		(2.940)	(2.768)	(2.328)
Life3		-0.291***	-0.230***	-0.351***
		(-4.306)	(-3.432)	(-4.367)
Life4		0.0966***	0.0877***	0.0654**
		(3.289)	(3.002)	(1.988)
pLife1			0.811***	0.777***
			(7.460)	(6.496)
pLife2			0.118	0.0122
			(1.639)	(0.166)
pLife3			-0.908***	-0.675***
			(-8.876)	(-6.075)
pLife4			0.0610**	-0.0108
			(2.014)	(-0.358)
Log Age	-0.927***	-0.617***	-0.578***	-0.746***
	(-7.930)	(-4.542)	(-4.293)	(-4.439)
Log 10-K Size	0.914***	1.014***	0.972***	0.942***
	(13.93)	(14.30)	(13.76)	(11.44)
Log Assets	1.217***	1.359***	1.346***	1.312***
	(9.878)	(10.50)	(10.43)	(9.218)
TNIC HHI	-0.251***	-0.226***	-0.210***	-0.168***
	(-6.358)	(-5.652)	(-5.370)	(-4.124)
Tobin's Q	-0.142***	-0.0909**	-0.128***	-0.163***
	(-4.547)	(-2.531)	(-3.581)	(-4.362)
Observations	103,606	90,122	89,987	69,461
R^2	0.811	0.821	0.822	0.828
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Text-based Measures of Competition Complaints

The table reports firm-year panel estimates for our sample of annual firm observations. An observation is one firm in one year. The dependent variable is a textual measure of competition complaints in 10-K filings. Base Comp measures competition in general. We have scaled the Base Comp variables by 1000. The product life cycle variables (Life1-Life4 and pLife1-pLife4) are based on textual analysis of 10-K statements using anchor-phrase queries in each year (Please see section 3 for details). Column (1) is based on firm age and other key control variables. Column (2) and (3) report results for a product life cycle versus competition complaint model. Column (2) is based on the four life cycle variables for focal firms (Life1-Life4). Column (3) is based on the eight life cycle variables (Life1-Life4 for focal firms; pLife1-pLife4 for peer firms based on TNIC-2 granularity). Column (4) shows the test result of eight life cycles that excludes financials (SIC codes 6000-6999) from the sample. All columns include firm and year fixed effects, and standard errors are clustered by firm. Key controls are included for all tests. All RHS variables are standardized. *t*-statistics are in parentheses.

	(1)	(2)	(3)	(4)
	Full Sample	Full Sample	Full Sample	Exclude Financials
VARIABLES	BaseComp x 1000	BaseComp x 1000	BaseComp x 1000	BaseComp x 1000
Life1		1.012***	0.935***	1.110***
		(6.491)	(6.045)	(6.893)
Life2		0.198	0.187	0.313**
		(1.503)	(1.418)	(2.423)
Life3		-0.497***	-0.407**	-0.553***
		(-2.613)	(-2.185)	(-2.752)
Life4		-0.0680	-0.0835	-0.157**
		(-1.037)	(-1.286)	(-2.278)
pLife1			1.186***	1.047***
			(5.997)	(4.981)
pLife2			0.0872	0.150
			(0.511)	(0.810)
pLife3			-1.369***	-1.232***
			(-7.781)	(-6.558)
pLife4			0.175***	0.132**
			(2.750)	(2.086)
Log Age	-2.375***	-2.281***	-2.208***	-2.000***
	(-8.245)	(-7.321)	(-7.205)	(-6.517)
Log 10-K Size	-7.188***	-6.086***	-6.148***	-5.519***
	(-7.511)	(-7.483)	(-7.505)	(-8.860)
Log Assets	3.150***	2.826***	2.813***	2.706***
	(10.08)	(9.666)	(9.525)	(9.631)
TNIC HHI	-0.815***	-0.748***	-0.723***	-0.701***
	(-8.519)	(-8.633)	(-8.442)	(-8.977)
Tobin's Q	0.357***	0.290***	0.234***	0.233***
	(6.015)	(4.492)	(3.633)	(3.449)
Observations	107,195	93,178	93,039	71,992
R^2	0.580	0.613	0.614	0.662
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Economic Magnitudes

The table reports economic magnitudes of the baseline disclosure results. In Panel A, we perform quintile sorts annually using the difference between Life1 and Life3 (Life1-Life3) and report the averages of each disclosure policy for the high and low (Life1-Life3) quintile as well as the inter-quintile range and its significance level. In Panel B, we conduct analogous quintile sorts annually using the peer life cycle exposures (pLife1-pLife3). To increase the intuitiveness of reported magnitudes, we standardize all of our continuous disclosure variables before reporting their quintile averages. Therefore, the inter-quartile range can be interpreted as the number of standard deviations the given disclosure variable shifts when moving from the first to the fifth (Life1-Life3) quintile. To further improve intuition, two of our disclosure policies variables (redaction and technology competition complaints) have a natural representation as dummy variables (Row 3 and Row 7), and we also report the average of these dummies across the quintiles.

		Panel A Quintiles Based on Own-Firm (Life1-Life3)			Panel B Quintiles Based on Peer-Firm (Life1-Life3)		
Row	Dependent Variable	Low Quintile	High Quintile	High-Low	Low Quintile	High Quintile	High-Low
1	Innovation Secrecy	-.034	.359	.393***	-.264	.314	.578***
2	Redaction	-.088	.352	.440***	-.167	.404	.571***
3	Redaction Dummy	.303	.546	.243***	.229	.569	.340***
4	Bog Index	-.040	.451	.491***	-.265	.617	.882***
5	Competition Complaints	-.042	.217	.259***	-.121	.231	.352***
6	Technology Competition	-.131	.455	.586***	-.243	.491	.734***
7	Technology Competition Dummy	.560	.815	.255***	.475	.824	.349***

Table 8: Firm Age, Rigidities, and Product Life Cycles

The table presents the interaction between product life cycles (PLC) and firm life cycles (FLC), measured using firm age. We add interactions between our text-based PLC measures (Life1-Life4) and firm age to our baseline regressions and the results are displayed here. To reduce multicollinearity and improve interpretation, we first standardize log age to have zero mean and unit standard deviation before running these regressions. Column (1) and (2) present the results for innovation secrecy. Column (3) and (4) present the results for information redaction. Column (5) and (6) present the results for financial reporting readability measured by Bog Index. Column (7) and (8) present the results for competition complaints. We include firm and year fixed effects, and standard errors are clustered by firm. All controls are included for all tests. *t*-statistics are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Innovation Secrecy x 100		Redaction x 1000		Bog Index		BaseComp x 1000	
VARIABLES	coef	tstat	coef	tstat	coef	tstat	coef	tstat
Life1	1.576***	(3.337)	0.333**	(2.539)	1.109***	(4.882)	3.527***	(6.264)
Life2	-0.627	(-1.461)	0.116	(1.366)	0.657***	(3.279)	0.475	(0.853)
Life3	-1.158**	(-2.512)	-0.324***	(-3.832)	-0.979***	(-4.287)	-1.550**	(-2.494)
Life4	0.490	(1.053)	0.0352	(0.512)	0.358**	(2.073)	-0.424	(-1.138)
Life1 x Log Age	-2.122***	(-4.678)	-0.506***	(-3.744)	-0.0704	(-0.332)	-1.102	(-1.526)
Life2 x Log Age	1.535***	(3.727)	0.0206	(0.304)	-0.301	(-1.604)	1.497**	(2.543)
Life3 x Log Age	0.770*	(1.809)	0.398***	(4.983)	0.118	(0.539)	-0.538	(-1.258)
Life4 x Log Age	0.318	(0.676)	0.00456	(0.0676)	0.349*	(1.950)	0.131	(0.306)
Log Age	-2.413***	(-6.396)	-0.145***	(-2.579)	-0.542***	(-3.725)	-2.095***	(-7.856)
Log 10-K Size	1.395***	(5.993)	-0.225***	(-3.421)	1.674***	(14.28)	-10.12***	(-7.440)
Log Assets	0.356**	(2.231)	0.0218	(1.154)	0.592***	(10.51)	1.228***	(9.687)
TNIC HHI	-1.871***	(-4.820)	-0.186*	(-1.750)	-0.833***	(-5.659)	-2.739***	(-8.646)
Tobin's Q	0.101**	(2.283)	0.0310***	(2.774)	-0.0410**	(-2.550)	0.127***	(4.346)
Observations	93,178		93,178		90,122		93,178	
R^2	0.770		0.595		0.821		0.613	
Controls	YES		YES		YES		YES	
Firm FE	YES		YES		YES		YES	
Year FE	YES		YES		YES		YES	

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Focal Firm and Peer Firm Interactive Effects

The table presents the interaction between focal firms and peer firms. We add interactions between focal firm life cycles and peer firm life cycles to our baseline regressions and the results are displayed here. Column (1) and (2) present the results for innovation secrecy. Column (3) and (4) present the results for information redaction. Column (5) and (6) present the results for financial reporting readability measured by Bog Index. Column (7) and (8) present the results for competition complaints. We include firm and year fixed effects, and standard errors are clustered by firm. All controls are included for all tests. *t*-statistics are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Innovation Secrecy x 100		Redaction x 1000		Bog Index		BaseComp x 1000	
VARIABLES	coef	tstat	coef	tstat	coef	tstat	coef	tstat
Life1	0.694	(1.424)	-0.0141	(-0.0944)	0.510**	(2.239)	2.662***	(5.050)
Life2	-0.174	(-0.408)	0.106	(1.125)	0.400**	(2.040)	0.619	(1.220)
Life3	-0.502	(-0.997)	0.0438	(0.487)	-0.202	(-0.855)	-0.865	(-1.443)
Life4	0.717*	(1.731)	0.0276	(0.415)	0.562***	(3.395)	-0.320	(-0.882)
pLife1	1.021***	(3.676)	-0.0179	(-0.393)	0.477***	(3.857)	0.875***	(3.927)
pLife2	-0.746***	(-3.613)	-0.00762	(-0.292)	-0.0336	(-0.379)	-0.0221	(-0.115)
pLife3	-0.544**	(-2.154)	-0.104***	(-2.642)	-0.592***	(-5.160)	-1.090***	(-5.732)
pLife4	-0.000407	(-0.00573)	0.0661***	(5.654)	0.0861***	(2.645)	0.212***	(3.074)
Life1 x pLife1	0.651**	(2.262)	0.467***	(5.239)	0.839***	(6.204)	0.773***	(2.829)
Life2 x pLife2	-0.194	(-0.711)	-0.0306	(-0.750)	0.334***	(2.768)	0.248	(1.071)
Life3 x pLife3	-0.627**	(-2.309)	-0.293***	(-4.258)	-0.641***	(-4.864)	-0.561**	(-2.175)
Life4 x pLife4	-0.398*	(-1.690)	-0.0875***	(-2.999)	-0.251***	(-2.776)	-0.351**	(-2.009)
Log Age	-2.583***	(-6.627)	-0.162***	(-3.009)	-0.660***	(-4.285)	-2.527***	(-7.242)
Log 10-K Size	1.310***	(5.637)	-0.243***	(-3.712)	1.599***	(13.59)	-10.21***	(-7.499)
Log Assets	0.347**	(2.173)	0.0238	(1.261)	0.586***	(10.48)	1.225***	(9.534)
TNIC HHI	-1.698***	(-4.393)	-0.188*	(-1.737)	-0.781***	(-5.427)	-2.673***	(-8.485)
Tobin's Q	0.0814*	(1.835)	0.0265**	(2.391)	-0.0620***	(-3.901)	0.101***	(3.500)
Observations	93,039		93,039		89,987		93,039	
R^2	0.770		0.596		0.822		0.615	
Controls	YES		YES		YES		YES	
Firm FE	YES		YES		YES		YES	
Year FE	YES		YES		YES		YES	

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10: Pairwise Search and Life Cycles

The table displays pairwise panel regressions in which the dependent variables are based on EDGAR Search of 10-K filings using the novel framework of Bernard, Blackburne, and Thornock (2019). The dependent variable captures the total number of search target's filings downloaded from the SEC's EDGAR database by searcher firm during year t (*Pariwise Search*) on firm-pair characteristics, searcher firm characteristics, and search target firm characteristics. We focus on the top 1000 largest firms based on firm sizes in each year. The product life cycle variables (Life1-Life4) are based on textual analysis of 10-K statements using anchor-phrase queries in each year (Please see section 3 for details). To interpret the RHS variables, the *LifeX Search LifeY* variable means that LifeX is the searching firm and LifeY is the search target. *LifeX Searcher* variable captures the product life cycle stage of the searcher firm. *LifeY Search Target* variable captures the product life cycle stage of the search target firm. We include *firm-pair* and year fixed effects, and standard errors are clustered by firm. Key controls are included for all tests. All RHS variables are standardized. t-statistics are in parentheses.

	(1)	(2)
	Pariwise Search	
VARIABLES	coef	tstat
Life1 Search Life1	0.0420***	(4.433)
Life2 Search Life2	-0.0177***	(-3.759)
Life3 Search Life3	0.0144**	(2.194)
Life4 Search Life4	0.000144	(0.192)
Life2 Search Life1	-0.00548	(-0.951)
Life3 Search Life1	-0.0293***	(-3.936)
Life4 Search Life1	-0.00643***	(-3.240)
Life1 Search Life2	-0.0145***	(-3.130)
Life3 Search Life2	0.0257***	(4.740)
Life4 Search Life2	-0.000677	(-0.492)
Life1 Search Life3	-0.0276***	(-3.513)
Life2 Search Life3	0.0189***	(3.064)
Life4 Search Life3	0.00714***	(3.997)
Life1 Search Life4	-0.00533*	(-1.791)
Life2 Search Life4	-0.00397*	(-1.761)
Life3 Search Life4	0.00650**	(2.561)
Life1 Search Target	-0.00947**	(-2.062)
Life2 Search Target	0.0101***	(2.660)
Life3 Search Target	-0.00578	(-1.489)
Life4 Search Target	0.00413*	(1.715)
Life1 Searcher	0.00263	(0.843)
Life2 Searcher	0.0120***	(5.741)
Life3 Searcher	-0.0237***	(-9.358)
Life4 Searcher	-0.00309***	(-3.489)
Score	0.0915***	(22.02)
bTNIC3	0.0420***	(13.85)
bTNIC2o3	0.0187***	(12.46)
Log Age (Search Target)	-0.0422***	(-4.747)
Tobin's Q (Search Target)	-0.0603***	(-3.739)
TNIC HHI (Search Target)	0.0120***	(4.820)
Log 10-K Size (Search Target)	-0.00109	(-0.334)
Log Assets (Search Target)	0.0411***	(4.171)
Log Age (Searcher)	-0.0374***	(-9.985)
Tobin's Q (Searcher)	-0.00274	(-0.694)
TNIC HHI (Searcher)	0.0102***	(16.99)
Log 10-K Size (Searcher)	0.00188**	(2.430)
Log Assets (Searcher)	0.0159***	(11.80)
Observations	11,277,172	
R^2	0.057	
FE	YES	
Controls	YES	

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 11: Patent Depreciation Waves and Disclosure Strategies

The table displays the baseline results of the patent expiration shock. The dependent variable is an innovation secrecy variable, which is calculated by dividing mentions of "trade secrets" by one plus the sum of the mentions of "patents" and of "trade secrets" in the filings. The other dependent variable is a redaction variable, which is calculated as the count of redaction words in 10-K filings based on Glaeser (2018) and Boone, Floros, and Johnson (2016). The product life cycle variables (Life1-Life4) are based on textual analysis of 10-K statements using anchor-phrase queries in each year (Please see section 3 for details). PatDepWave measure is based on all patents. Column (1) & (4), Column (2) & (5), and Column (3) & (6) separately report the results based on the SIC-2, SIC-3 and SIC-2o3 level patent depreciation wave measures. We include firm and year fixed effects, and standard errors are clustered by firm. All controls are included for all tests. All RHS variables are standardized. *t*-statistics are in parentheses.

VARIABLES	(1) Innovation Secrecy x 100	(2) Innovation Secrecy x 100	(3) Innovation Secrecy x 100	(4) Redaction x 1000	(5) Redaction x 1000	(6) Redaction x 1000
Life1	0.326**	0.338**	0.337**	0.0597	0.0664	0.0617
	(2.276)	(2.367)	(2.350)	(1.330)	(1.474)	(1.368)
Life2	-0.0900	-0.0848	-0.0973	0.0330	0.0342	0.0333
	(-0.825)	(-0.781)	(-0.892)	(1.452)	(1.509)	(1.458)
Life3	-0.265*	-0.285**	-0.276**	-0.0690***	-0.0738***	-0.0724***
	(-1.939)	(-2.078)	(-2.015)	(-2.856)	(-2.997)	(-2.943)
Life4	0.122*	0.125*	0.124*	0.00643	0.00462	0.00619
	(1.654)	(1.697)	(1.685)	(0.564)	(0.407)	(0.538)
SIC2 PatDepWave	-0.302*			0.0547**		
	(-1.760)			(2.360)		
Life1 x SIC2 PatDepWave	0.894***			0.220***		
	(4.926)			(4.098)		
Life2 x SIC2 PatDepWave	-0.0957			-0.0548*		
	(-0.601)			(-1.672)		
Life3 x SIC2 PatDepWave	-0.879***			-0.0982**		
	(-5.154)			(-2.304)		
Life4 x SIC2 PatDepWave	0.0281			-0.0181		
	(0.394)			(-1.500)		
SIC3 PatDepWave		-0.418**			0.0666**	
		(-2.408)			(2.324)	
Life1 x SIC3 PatDepWave		0.738***			0.147***	
		(3.897)			(2.756)	
Life2 x SIC3 PatDepWave		0.0903			-0.0358	
		(0.524)			(-0.936)	
Life3 x SIC3 PatDepWave		-0.725***			-0.0578	
		(-3.818)			(-1.230)	
Life4 x SIC3 PatDepWave		-0.000751			-0.0192	
		(-0.0114)			(-1.416)	
SIC2o3 PatDepWave			-0.304*			0.0481*
			(-1.837)			(1.895)
Life1 x SIC2o3 PatDepWave			0.889***			0.223***
			(5.012)			(4.037)
Life2 x SIC2o3 PatDepWave			0.0283			-0.0612*
			(0.174)			(-1.881)
Life3 x SIC2o3 PatDepWave			-0.924***			-0.103**
			(-5.386)			(-2.330)
Life4 x SIC2o3 PatDepWave			0.00940			-0.0126
			(0.135)			(-1.094)
Observations	93,167	93,161	93,167	93,167	93,161	93,167
R^2	0.770	0.770	0.770	0.595	0.595	0.595
Controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 12: Patent Depreciation Waves and Disclosure Strategies

The table displays the baseline results of the patent expiration shock. The dependent variable Bog Index is a plain English measure of financial reporting readability based on Bonsall, Leone, Miller, and Rennekamp, (2017), which is a multifaceted index designed to capture a broad set of plain English attributes. The other dependent variable is a specific textual measure of IP competition complaints in 10-K filings. The product life cycle variables (Life1-Life4) are based on textual analysis of 10-K statements using anchor-phrase queries in each year (Please see section 3 for details). PatDepWave measure is based on all patents. Column (1) & (4), Column (2) & (5), and Column (3) & (6) separately report the results based on the SIC-2, SIC-3 and SIC-2o3 level patent depreciation wave measures. We include firm and year fixed effects, and standard errors are clustered by firm. All controls are included for all tests. All RHS variables are standardized. *t*-statistics are in parentheses.

VARIABLES	(1) Bog Index	(2) Bog Index	(3) Bog Index	(4) CompIP x 1000	(5) CompIP x 1000	(6) CompIP x 1000
Life1	0.291***	0.309***	0.295***	0.304***	0.317***	0.306***
	(4.226)	(4.482)	(4.279)	(5.114)	(5.362)	(5.125)
Life2	0.142***	0.149***	0.143***	0.167***	0.167***	0.167***
	(2.815)	(2.951)	(2.824)	(2.963)	(2.978)	(2.966)
Life3	-0.246***	-0.263***	-0.251***	-0.595***	-0.608***	-0.601***
	(-3.630)	(-3.885)	(-3.713)	(-5.925)	(-6.019)	(-5.978)
Life4	0.102***	0.0984***	0.102***	0.102***	0.100***	0.104***
	(3.452)	(3.334)	(3.437)	(3.400)	(3.328)	(3.479)
SIC2 PatDepWave	0.0363			0.180***		
	(0.544)			(3.202)		
Life1 x SIC2 PatDepWave	0.467***			0.366***		
	(5.414)			(4.395)		
Life2 x SIC2 PatDepWave	0.0207			-0.120*		
	(0.266)			(-1.682)		
Life3 x SIC2 PatDepWave	-0.284***			-0.210***		
	(-3.487)			(-2.796)		
Life4 x SIC2 PatDepWave	-0.0449			-0.00264		
	(-1.334)			(-0.0774)		
SIC3 PatDepWave		0.0929			0.142**	
		(1.293)			(2.457)	
Life1 x SIC3 PatDepWave		0.266***			0.167	
		(2.768)			(1.496)	
Life2 x SIC3 PatDepWave		0.0171			-0.00623	
		(0.212)			(-0.0692)	
Life3 x SIC3 PatDepWave		-0.127			-0.0804	
		(-1.592)			(-1.055)	
Life4 x SIC3 PatDepWave		-0.0491			-0.0187	
		(-1.160)			(-0.409)	
SIC2o3 PatDepWave			0.0166			0.166***
			(0.238)			(2.875)
Life1 x SIC2o3 PatDepWave			0.520***			0.376***
			(6.139)			(4.960)
Life2 x SIC2o3 PatDepWave			-0.0369			-0.121*
			(-0.477)			(-1.798)
Life3 x SIC2o3 PatDepWave			-0.334***			-0.220***
			(-4.171)			(-3.025)
Life4 x SIC2o3 PatDepWave			-0.0356			-0.0195
			(-1.137)			(-0.604)
Observations	90,112	90,106	90,112	93,167	93,161	93,167
R^2	0.821	0.821	0.821	0.663	0.663	0.663
Controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 13: Strategic Disclosure Quality in Conference Calls

The table reports firm-year panel estimates for our sample of annual firm observations. An observation is one firm in one year. The dependent variable is a disclosure quality variable of company earnings calls, which is calculated as [1 - Cosine Similarity between Firm Call Presentation and Average Text of Call Presentation by SIC-2 peers in the same year] based on Hanley and Hoberg (2010). We have scaled the conference call variables by 100. Transcripts with fewer than 250 words and firms with fewer than 25 peers are excluded. The product life cycle variables (Life1-Life4 and pLife1-pLife4) are based on textual analysis of 10-K statements using anchor-phrase queries in each year (Please see section 3 for details). Column (1) is based on the four life cycle variables for focal firms (Life1-Life4). Column (2) is based on the eight life cycle variables (Life1-Life4 for focal firms; pLife1-pLife4 for peer firms based on TNIC-2 granularity). Column (1) and (2) report results for a product life cycle versus conference call disclosure quality model. Column (3) shows the test result of eight life cycles that excludes financials (SIC codes 6000-6999) from the sample. All columns include firm and year fixed effects, and standard errors are clustered by firm. Key controls are included for all tests. All RHS variables are standardized. *t*-statistics are in parentheses.

	(1)	(2)	(3)
	Full Sample	Full Sample	Exclude Financials
VARIABLES	ConfCallDisQuality	ConfCallDisQuality	ConfCallDisQuality
	x 100	x 100	x 100
Life1	-0.970***	-0.968***	-1.028***
	(-3.127)	(-3.125)	(-2.993)
Life2	0.265	0.275	0.147
	(1.364)	(1.414)	(0.677)
Life3	0.809***	0.754***	0.827***
	(3.029)	(2.825)	(2.949)
Life4	0.131	0.156	0.170
	(1.155)	(1.369)	(1.351)
pLife1		-0.469	-0.593
		(-1.135)	(-1.355)
pLife2		0.374	0.214
		(1.251)	(0.709)
pLife3		0.849**	1.248***
		(2.316)	(3.351)
pLife4		-0.198*	-0.305***
		(-1.847)	(-2.758)
Log Age	0.115	-0.00604	0.539
	(0.239)	(-0.0125)	(1.004)
Log 10-K Size	-0.206	-0.159	-0.284
	(-1.100)	(-0.847)	(-1.430)
Log Assets	-1.588***	-1.587***	-1.859***
	(-3.613)	(-3.614)	(-3.945)
TNIC HHI	0.339***	0.321***	0.268**
	(3.170)	(3.009)	(2.528)
Tobin's Q	-0.00683	0.00627	-0.0587
	(-0.0384)	(0.0351)	(-0.317)
Observations	29,431	29,431	24,027
R^2	0.851	0.851	0.829
Firm FE	YES	YES	YES
Year FE	YES	YES	YES

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14: Patent Depreciation Waves and Conference Calls

The table displays the baseline results of the patent expiration shock. The dependent variable is a disclosure quality variable of company earnings calls, which is calculated as [1 - Cosine Similarity between Firm Call Presentation and Average Text of Call Presentation by SIC-2 peers in the same year] based on Hanley and Hoberg (2010). We have scaled the conference call variables by 100. Transcripts with fewer than 250 words and firms with fewer than 25 peers are excluded. The product life cycle variables (Life1-Life4) are based on textual analysis of 10-K statements using anchor-phrase queries in each year (Please see section 3 for details). PatDepWave measure is based on all patents. Column (1), Column (2), and Column (3) separately report the results based on the SIC-2, SIC-3 and SIC-2o3 level patent depreciation wave measures. We include firm and year fixed effects, and standard errors are clustered by firm. All controls are included for all tests. All RHS variables are standardized. *t*-statistics are in parentheses.

	(1)	(2)	(3)
VARIABLES	ConfCallDisQuality x 100	ConfCallDisQuality x 100	ConfCallDisQuality x 100
Life1	-0.964***	-0.952***	-0.941***
	(-3.077)	(-3.013)	(-2.982)
Life2	0.287	0.275	0.281
	(1.482)	(1.424)	(1.441)
Life3	0.788***	0.779***	0.772***
	(2.941)	(2.884)	(2.860)
Life4	0.124	0.125	0.124
	(1.099)	(1.097)	(1.093)
SIC2 PatDepWave	0.014		
	(0.090)		
Life1 x SIC2 PatDepWave	-0.810**		
	(-2.364)		
Life2 x SIC2 PatDepWave	0.198		
	(0.703)		
Life3 x SIC2 PatDepWave	0.693**		
	(2.209)		
Life4 x SIC2 PatDepWave	0.003		
	(0.027)		
SIC3 PatDepWave		-0.085	
		(-0.475)	
Life1 x SIC3 PatDepWave		-0.690*	
		(-1.899)	
Life2 x SIC3 PatDepWave		-0.029	
		(-0.096)	
Life3 x SIC3 PatDepWave		0.729**	
		(2.324)	
Life4 x SIC3 PatDepWave		0.024	
		(0.204)	
SIC2o3 PatDepWave			0.039
			(0.232)
Life1 x SIC2o3 PatDepWave			-1.015***
			(-2.829)
Life2 x SIC2o3 PatDepWave			0.390
			(1.243)
Life3 x SIC2o3 PatDepWave			0.717**
			(2.105)
Life4 x SIC2o3 PatDepWave			0.027
			(0.235)
Observations	29,452	29,447	29,452
R^2	0.851	0.851	0.851
Controls	YES	YES	YES
Firm FE	YES	YES	YES
Year FE	YES	YES	YES

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 1: Visualization of Quasi-experiment: Technological Depreciation Waves. We measure innovative activity at the sector level over long, and deeply lagged windows. As patents are typically valid for 20 years in our sample, we first form two windows: an "early" window that includes years [t-11 to t-19] and a "late" window that includes years [t-2 to t-10]. The additional two year lag in the late window is to ensure both periods are deeply lagged.

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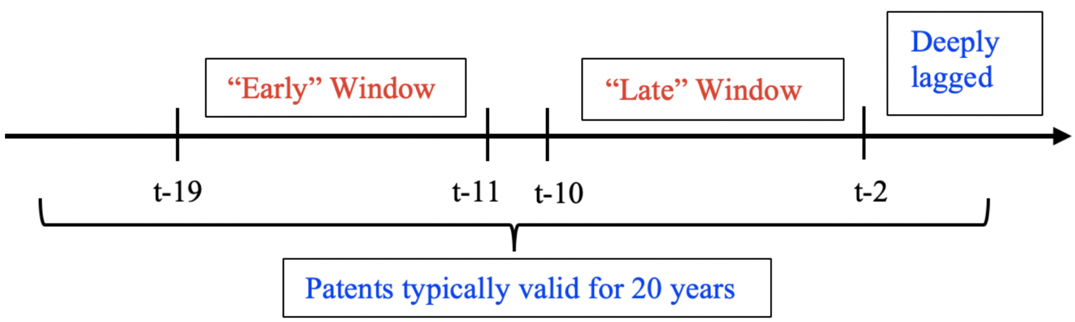
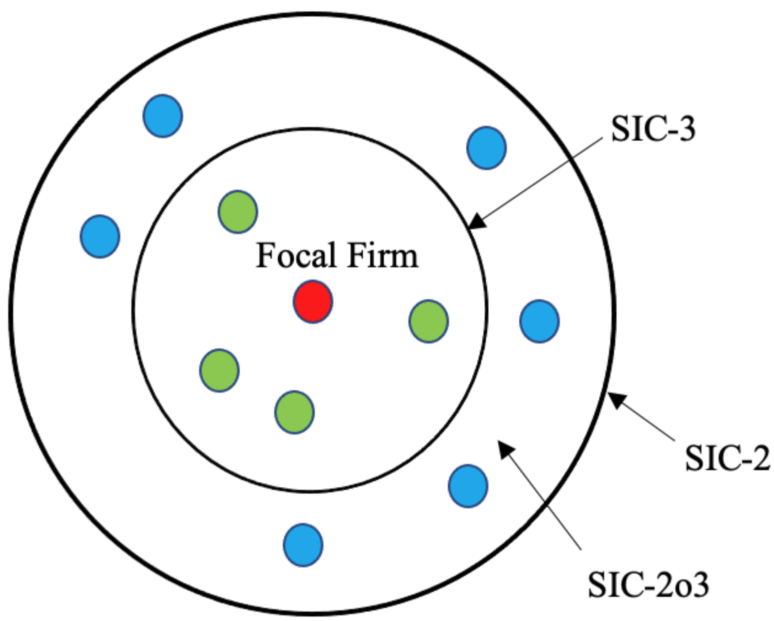


Figure 2: Inter-Firm Relations in the Product Market Space: This figure shows an example of a product market space with different granularity. The focal firm at the center has closely linked product market peers (SIC-3) in the inner circle, and also distant product industry peers (SIC-2o3) outside the inner circle but inside the outer circle.



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Online Appendix

Life Cycles of Firm Disclosures

Not Intended for Publication

Table A1: Text-based Measures of Competition for IP and High Competition

The table reports firm-year panel estimates for our sample of annual firm observations. An observation is one firm in one year. The dependent variables are specific textual measures of competition complaints in 10-K filings. We search for two types of complaints in the 10-K filings here. Comp IP measures complaints about intellectual property competition; Comp High measures complaints about competition with high intensity. We have scaled the dependent variables by 1000. The product life cycle variables (Life1-Life4 and pLife1-pLife4) are based on textual analysis of 10-K statements using anchor-phrase queries in each year (Please see section 3 for details). Column (1) and (2) are based on firm age and other key control variables. Column (3)-(6) report results for a product life cycle versus competition complaint model. Column (3) and (4) are based on the four life cycle variables for focal firms (Life1-Life4). Column (5) and (6) are based on the eight life cycle variables (Life1-Life4 for focal firms; pLife1-pLife4 for peer firms based on TNIC-2 granularity). Column (7) and (8) show the test results of eight life cycles that exclude financials (SIC codes 6000-6999) from the sample. All columns include firm and year fixed effects, and standard errors are clustered by firm. Key controls are included for all tests. All RHS variables are standardized. *t*-statistics are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Full	Full	Full	Full	Full	Full	No Financials	No Financials
VARIABLES	CompIP	CompHigh	CompIP	CompHigh	CompIP	CompHigh	CompIP	CompHigh
	x 1000	x 1000	x 1000	x 1000	x 1000	x 1000	x 1000	x 1000
Life1			0.342***	0.494***	0.303***	0.430***	0.388***	0.413***
			(5.635)	(4.327)	(5.062)	(3.785)	(4.927)	(4.387)
Life2			0.166***	0.230**	0.159***	0.230**	0.151**	0.287***
			(2.937)	(2.222)	(2.943)	(2.204)	(2.218)	(3.671)
Life3			-0.631***	-0.777***	-0.575***	-0.709***	-0.668***	-0.685***
			(-6.238)	(-4.897)	(-5.904)	(-4.586)	(-5.539)	(-4.543)
Life4			0.100***	0.0874*	0.0903***	0.0735*	0.0943***	0.0536
			(3.324)	(1.938)	(3.025)	(1.661)	(2.713)	(1.267)
pLife1					0.569***	1.041***	0.478***	0.933***
					(4.715)	(9.093)	(3.695)	(7.983)
pLife2					-0.00297	-0.127	-0.0348	-0.173
					(-0.0252)	(-1.144)	(-0.258)	(-1.532)
pLife3					-0.770***	-1.053***	-0.636***	-0.814***
					(-9.088)	(-8.729)	(-6.843)	(-6.849)
pLife4					0.0687**	0.146***	0.0581*	0.127***
					(2.153)	(4.101)	(1.732)	(4.062)
Log Age	-1.056***	-1.663***	-0.822***	-1.454***	-0.775***	-1.395***	-1.043***	-1.584***
	(-7.757)	(-7.051)	(-8.120)	(-6.027)	(-7.898)	(-5.903)	(-8.063)	(-8.840)
Log 10-K Size	-2.808***	-4.653***	-1.950***	-3.682***	-1.982***	-3.729***	-2.264***	-3.255***
	(-4.087)	(-4.751)	(-5.018)	(-4.481)	(-5.077)	(-4.504)	(-4.796)	(-5.218)
Log Assets	1.397***	1.807***	1.184***	1.562***	1.186***	1.540***	1.306***	1.437***
	(6.484)	(6.685)	(8.197)	(6.432)	(8.109)	(6.262)	(7.681)	(6.765)
TNIC HHI	-0.275***	-0.384***	-0.232***	-0.342***	-0.219***	-0.319***	-0.230***	-0.307***
	(-5.891)	(-4.931)	(-6.432)	(-5.099)	(-6.111)	(-4.790)	(-6.104)	(-5.937)
Tobin's Q	0.237***	0.240***	0.239***	0.194***	0.211***	0.149***	0.200***	0.135***
	(6.448)	(6.209)	(6.267)	(4.829)	(5.556)	(3.732)	(5.116)	(3.333)
Observations	107,195	107,195	93,178	93,178	93,039	93,039	71,992	71,992
R^2	0.507	0.427	0.662	0.441	0.664	0.443	0.660	0.538
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A2: High-value Patent Depreciation Waves and Disclosure Strategies

The table displays the baseline results of the patent expiration shock. The dependent variable is an innovation secrecy variable, which is calculated by dividing mentions of "trade secrets" by the sum of one plus the mentions of "patents" and of "trade secrets" in the filings. The other dependent variable is a redaction variable, which is calculated as the count of redaction words in 10-K filings based on Glaeser (2018) and Boone, Floros, and Johnson (2016). The product life cycle variables (Life1-Life4) are based on textual analysis of 10-K statements using anchor-phrase queries in each year (Please see section 3 for details). High-value patent depreciation wave variable (PatDepWaveHV) focuses on only high-value patents whose KPSS value divided by market value of the firm is above the median. Column (1) & (4), Column (2) & (5), and Column (3) & (6) separately report the results based on the SIC-2, SIC-3 and SIC-2o3 level patent depreciation wave measures. We include firm and year fixed effects, and standard errors are clustered by firm. All controls are included for all tests. All RHS variables are standardized. t-statistics are in parentheses.

VARIABLES	(1) Innovation Secrecy x 100	(2) Innovation Secrecy x 100	(3) Innovation Secrecy x 100	(4) Redaction x 1000	(5) Redaction x 1000	(6) Redaction x 1000
Life1	0.335**	0.352**	0.333**	0.0591	0.0685	0.0589
	(2.330)	(2.462)	(2.310)	(1.306)	(1.506)	(1.282)
Life2	-0.0822	-0.0802	-0.0846	0.0319	0.0318	0.0336
	(-0.756)	(-0.739)	(-0.777)	(1.402)	(1.399)	(1.463)
Life3	-0.282**	-0.308**	-0.281**	-0.0663***	-0.0718***	-0.0700***
	(-2.067)	(-2.249)	(-2.050)	(-2.734)	(-2.873)	(-2.813)
Life4	0.130*	0.129*	0.130*	0.00605	0.00416	0.00581
	(1.760)	(1.751)	(1.769)	(0.532)	(0.366)	(0.505)
SIC2 PatDepWaveHV	-0.211			0.0482**		
	(-1.223)			(2.015)		
Life1 x SIC2 PatDepWaveHV	0.836***			0.249***		
	(4.159)			(4.233)		
Life2 x SIC2 PatDepWaveHV	-0.155			-0.0577*		
	(-0.923)			(-1.758)		
Life3 x SIC2 PatDepWaveHV	-0.933***			-0.107**		
	(-4.885)			(-2.259)		
Life4 x SIC2 PatDepWaveHV	0.0461			-0.0305*		
	(0.600)			(-1.942)		
SIC3 PatDepWaveHV		-0.276*			0.0600*	
		(-1.680)			(1.807)	
Life1 x SIC3 PatDepWaveHV		0.649***			0.193***	
		(3.291)			(3.153)	
Life2 x SIC3 PatDepWaveHV		0.0976			-0.0666	
		(0.505)			(-1.605)	
Life3 x SIC3 PatDepWaveHV		-0.866***			-0.0799	
		(-4.382)			(-1.337)	
Life4 x SIC3 PatDepWaveHV		0.0254			-0.0188	
		(0.343)			(-1.222)	
SIC2o3 PatDepWaveHV			-0.155			0.0496**
			(-0.960)			(2.147)
Life1 x SIC2o3 PatDepWaveHV			0.828***			0.219***
			(4.378)			(3.883)
Life2 x SIC2o3 PatDepWaveHV			-0.127			-0.0467
			(-0.746)			(-1.587)
Life3 x SIC2o3 PatDepWaveHV			-0.912***			-0.0936**
			(-4.899)			(-2.107)
Life4 x SIC2o3 PatDepWaveHV			0.0343			-0.0236*
			(0.459)			(-1.690)
Observations	93,167	93,161	93,167	93,167	93,161	93,167
R^2	0.770	0.770	0.770	0.595	0.595	0.595
Controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A3: High-value Patent Depreciation Waves and Disclosure Strategies

The table displays the baseline results of the patent expiration shock. The dependent variable Bog Index is a plain English measure of financial reporting readability based on Bonsall, Leone, Miller, and Rennekamp, (2017), which is a multifaceted index designed to capture a broad set of plain English attributes. The other dependent variable is a specific textual measure of IP competition complaints in 10-K filings. The product life cycle variables (Life1-Life4) are based on textual analysis of 10-K statements using anchor-phrase queries in each year (Please see section 3 for details). High-value patent depreciation wave variable (PatDepWaveHV) focuses on only high-value patents whose KPSS value divided by market value of the firm is above the median. Column (1) & (4), Column (2) & (5), and Column (3) & (6) separately report the results based on the SIC-2, SIC-3 and SIC-2o3 level patent depreciation wave measures. We include firm and year fixed effects, and standard errors are clustered by firm. All controls are included for all tests. All RHS variables are standardized. *t*-statistics are in parentheses.

VARIABLES	(1) Bog Index	(2) Bog Index	(3) Bog Index	(4) CompIP x 1000	(5) CompIP x 1000	(6) CompIP x 1000
Life1	0.296***	0.313***	0.295***	0.305***	0.318***	0.302***
	(4.311)	(4.546)	(4.274)	(5.155)	(5.343)	(5.094)
Life2	0.143***	0.146***	0.148***	0.165***	0.163***	0.169***
	(2.834)	(2.882)	(2.935)	(2.923)	(2.898)	(2.988)
Life3	-0.252***	-0.264***	-0.258***	-0.592***	-0.603***	-0.596***
	(-3.741)	(-3.904)	(-3.813)	(-5.891)	(-5.964)	(-5.919)
Life4	0.100***	0.0972***	0.101***	0.1000***	0.0975***	0.102***
	(3.397)	(3.307)	(3.396)	(3.307)	(3.241)	(3.374)
SIC2 PatDepWaveHV	-0.0207			0.176***		
	(-0.318)			(3.178)		
Life1 x SIC2 PatDepWaveHV	0.411***			0.412***		
	(4.769)			(5.070)		
Life2 x SIC2 PatDepWaveHV	0.0546			-0.134*		
	(0.691)			(-1.893)		
Life3 x SIC2 PatDepWaveHV	-0.177**			-0.248***		
	(-2.130)			(-3.336)		
Life4 x SIC2 PatDepWaveHV	-0.0759**			-0.00183		
	(-2.428)			(-0.0572)		
SIC3 PatDepWaveHV		-0.0201			0.123**	
		(-0.309)			(2.357)	
Life1 x SIC3 PatDepWaveHV		0.306***			0.266***	
		(3.596)			(3.151)	
Life2 x SIC3 PatDepWaveHV		0.0591			-0.0536	
		(0.804)			(-0.624)	
Life3 x SIC3 PatDepWaveHV		-0.122			-0.137**	
		(-1.515)			(-1.973)	
Life4 x SIC3 PatDepWaveHV		-0.0684**			0.00475	
		(-2.275)			(0.143)	
SIC2o3 PatDepWaveHV			-0.0105			0.181***
			(-0.174)			(3.513)
Life1 x SIC2o3 PatDepWaveHV			0.416***			0.390***
			(5.118)			(5.306)
Life2 x SIC2o3 PatDepWaveHV			-0.0572			-0.132**
			(-0.760)			(-2.063)
Life3 x SIC2o3 PatDepWaveHV			-0.162**			-0.246***
			(-2.023)			(-3.522)
Life4 x SIC2o3 PatDepWaveHV			-0.0526*			-0.0167
			(-1.712)			(-0.531)
Observations	90,112	90,106	90,112	93,167	93,161	93,167
R^2	0.821	0.821	0.821	0.663	0.663	0.663
Controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A4: Life Cycles of Disclosures Using Dickinson (2011) Measures

The table displays the baseline results using Dickinson (2011) life cycle measures. The life cycle variables (D_Life1-D_Life5) are based on cash flow patterns of the a firm (Please refer to Dickinson [2011] for details). We include firm and year fixed effects, and standard errors are clustered by firm. All controls are included for all tests. *t*-statistics are in parentheses.

	(1)	(2)	(3)	(4)
VARIABLES	Innovation Secrecy x 100	Redaction x 1000	Bog Index	BaseComp x 1000
D_Life1	0.374**	0.0380	0.158**	0.395***
	(2.199)	(0.975)	(2.229)	(2.656)
D_Life2	0.0483	-0.0674*	-0.187***	0.0543
	(0.354)	(-1.779)	(-3.493)	(0.319)
D_Life3	0.0919	-0.0270	-0.321***	-0.0819
	(0.646)	(-0.831)	(-6.074)	(-0.417)
D_Life5	-0.0959	-0.0206	0.381***	0.123
	(-0.497)	(-0.524)	(4.635)	(0.619)
Log Age	-2.592***	-0.323***	-1.041***	-2.628***
	(-7.514)	(-5.739)	(-7.844)	(-8.096)
Log 10-K Size	0.977***	-0.232***	0.911***	-6.969***
	(6.969)	(-2.664)	(12.83)	(-6.965)
Log Assets	0.732**	0.0850	1.270***	3.121***
	(2.094)	(1.507)	(9.986)	(9.447)
TNIC HHI	-0.607***	-0.0587**	-0.244***	-0.747***
	(-6.045)	(-2.313)	(-6.185)	(-7.958)
Tobin's Q	0.289***	0.0606***	-0.165***	0.336***
	(3.411)	(2.895)	(-5.179)	(5.567)
Observations	100,838	100,838	97,455	100,838
R^2	0.764	0.579	0.816	0.608
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A5: Correlations with Dickinson (2011) Life Cycle Stages

The table displays the correlations between the text-based product life cycle measures in the current paper and the Dickinson (2011) life cycle stages. The product life cycle variables (Life1-Life4) are based on textual analysis of 10-K statements using anchor-phrase queries in each year (Please see section 3 for details). The life cycle variables (D_Life1-D_Life5) are based on cash flow patterns of the a firm (Please refer to Dickinson [2011] for details).

Variables	Life1	Life2	Life3	Life4	D_Life1	D_Life2	D_Life3	D_Life4	D_Life5
Life1	1.000								
Life2	0.583	1.000							
Life3	0.795	0.604	1.000						
Life4	0.399	0.443	0.415	1.000					
D_Life1	0.101	-0.009	-0.020	-0.036	1.000				
D_Life2	-0.046	-0.017	-0.001	-0.049	-0.307	1.000			
D_Life3	-0.039	0.079	0.059	0.045	-0.315	-0.480	1.000		
D_Life4	-0.031	-0.045	-0.015	0.040	-0.147	-0.225	-0.231	1.000	
D_Life5	0.056	-0.035	-0.044	0.017	-0.124	-0.189	-0.194	-0.091	1.000

Table A6: Life Cycles of Disclosures and Financial Constraints

The table presents the robustness tests based on financial constraint measures. Our financial constraint measures are based on Hoberg and Maksimovic (2015). Our measure of *Financial Constraint* is defined to capture that firms face liquidity challenges leading to potential underinvestment. Firms with higher *Financial Constraint* values are more similar to a set of firms known to be at risk of delaying their investments due to issues with liquidity. We also include corresponding dummies to more properly deal with missing value observations based on the financial constraint data. We include firm and year fixed effects, and standard errors are clustered by firm. All controls are included for all tests. All RHS variables are standardized. *t*-statistics are in parentheses.

	(1)	(2)	(3)	(4)
VARIABLES	Innovation Secrecy x 100	Redaction x 1000	Bog Index	CompIP x 1000
Life1	0.290**	0.0729**	0.281***	0.272***
	(2.080)	(2.048)	(4.140)	(4.546)
Life2	-0.0148	0.0273	0.140***	0.169***
	(-0.139)	(1.245)	(2.808)	(3.009)
Life3	-0.277**	-0.0634**	-0.241***	-0.559***
	(-2.066)	(-2.558)	(-3.651)	(-5.634)
Life4	0.113	-0.00300	0.0741**	0.0839***
	(1.605)	(-0.279)	(2.528)	(2.799)
pLife1	1.358***	0.204***	0.856***	0.603***
	(5.414)	(5.536)	(7.526)	(4.490)
pLife2	-0.772***	-0.0230	0.134*	-0.000516
	(-4.722)	(-1.007)	(1.829)	(-0.00407)
pLife3	-0.909***	-0.258***	-0.962***	-0.774***
	(-4.136)	(-6.933)	(-9.156)	(-8.764)
pLife4	-0.0312	0.0522***	0.0513*	0.0578*
	(-0.485)	(4.949)	(1.703)	(1.806)
Log Age	-2.215***	-0.160***	-0.687***	-0.786***
	(-6.439)	(-3.390)	(-4.875)	(-7.532)
Log 10-K Size	0.820***	-0.148***	0.937***	-2.070***
	(5.931)	(-3.605)	(13.39)	(-5.024)
Log Assets	0.848**	0.0311	1.319***	1.257***
	(2.306)	(0.631)	(9.957)	(8.160)
TNIC HHI	-0.443***	-0.0424	-0.201***	-0.218***
	(-4.117)	(-1.457)	(-4.976)	(-5.712)
Tobin's Q	0.163*	0.0604***	-0.125***	0.210***
	(1.652)	(2.578)	(-3.481)	(5.421)
Financial Constraint	0.129	0.0573***	-0.196***	0.173***
	(1.503)	(3.444)	(-6.039)	(5.160)
Dummy	-0.195	-0.0324	0.123	-0.201**
	(-0.829)	(-0.992)	(1.405)	(-2.155)
Observations	85,527	85,527	82,816	85,527
R^2	0.775	0.606	0.817	0.658
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1